

Weed Detection and Reduction of Herbicides by Agronomic Image Processing

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ABSTRACT: Agriculture is the backbone of human sustenance in this world. Now a days with growing population we need the productivity of the agriculture to be increased. So, the usage of deadly poisonous as herbicides has increased to a drastic level. Our aim is to increase the productivity but we have forgot about the damage done to the environment. In this project we deal with the reduction of herbicides by spraying them apart from the weed areas present. This weed areas detection in the fields is done by applying GLCM approach. Feature Extraction is a method of capturing visual content of images for indexing & retrieval. Primitive or low level image features can be either general features, such as extraction of colour, texture and shape or domain specific features. This paper presents an application of gray level co-occurrence matrix (GLCM) to extract second order statistical texture features for motion estimation of images. The Four features namely, Angular Second Moment, Correlation, Inverse Difference Moment, and Entropy are computed using Xilinx FPGA. The results show that these texture features have high discrimination accuracy, efficiently used for real time Pattern recognition applications.

KEYWORDS: Simulated images, Texture, gobber filter, Pattern recognition, Features, Frames.

I.INTRODUCTION

For site-specific weed management, many online systems using different optical sensors have been developed to enable spraying specifically the weed-infested areas. we propose an application of this modelling dedicated to images without perspective and assess the effectiveness of two crop/inter-row weed detection algorithms based on Gabor filtering or Hough transform. Then, for images with perspective effects, a crop/weed discrimination algorithm based on the Hough transform was analysed and tested on real images. it will take a very long time for either a manual segmentation of the image or a manual counting of weed plants in the field. Very few articles have reported on the evaluation of the robustness of crop/weed discrimination algorithms which have actually been validated from real images with natural weed patterns taken from a camera under natural outdoor lighting conditions (Andreasen et al. 1997; Tang et al. 1999; Onyango and Marchant 2005). Some algorithms have been developed in our lab and have been tested on real data and in real in-field conditions but assessing and comparing them appeared difficult and uncertain .

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Texture tactile or visual characteristic of a surface. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects. Though texture plays a significant role in image analysis and pattern recognition, only a few architectures implement on-board textural feature extraction. In this paper, Gray level co-occurrence matrix is formulated to obtain statistical texture features. A number of texture features may be extracted from the GLCM. Only four second order features namely angular second moment,

correlation, inverse difference moment, and entropy are computed. These four measures provide high discrimination accuracy required for motion picture estimation. These features are calculated and implemented using Xilinx ISE 13.4.

The main application of this model is Environmental assessment and monitoring, Imaging techniques with different spectrum such as infrared, hyper spectral imaging, X-ray were useful in vegetation indices, canopy measurements ,irrigated land mapping etc with greater accuracies, Fruit& food grading, because of increased expectations in quality food and safety standards.

II.HOUGH TRANSFORM

Hough transformation is a technique which can be used to isolate features of a particular shape within an image. The crop/weed discrimination algorithm is firstly based on crop row detection from the vanishing point (Hough Transform) and secondly based on crop/weed segmentation (region-based segmentation) for crop/weed pixel classification. In this case, we can't get a very high degree (up to 90%) of accuracy for this algorithm. In order to overcome this we go for GLCM method.

III.EXTRACTION OF GLCM

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Concurrence Matrix (GLCM) method is a way of extracting second order statistical texture features.

The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G , in the image. The matrix element $P(i, j | \Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance $(\Delta x, \Delta y)$, occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element $P(i, j | d, \theta)$ contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ) . Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a $G \times G$ matrix for each combination of $(\Delta x, \Delta y)$ or (d, θ) . Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel).

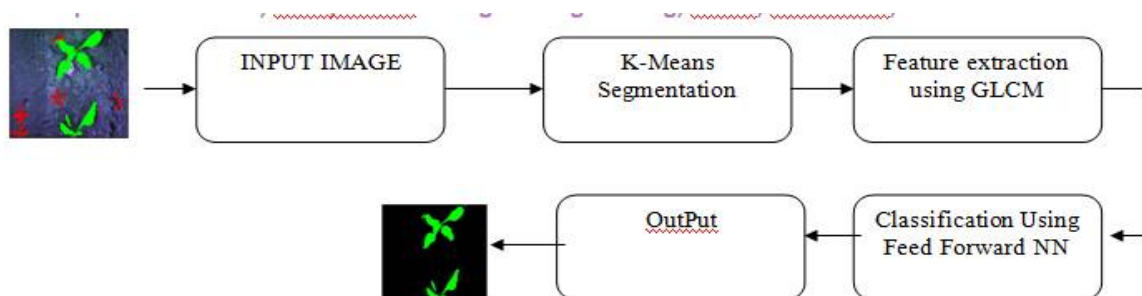


Figure 1: Block Diagram Of GLCM Method

neighbour pixel value --->	0	1	2	3
ref pixel value:				
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

The MATLAB code used for the GLCM is

```
q1 = imread('Jerry.jpg');
w1 = rgb2gray(q1);
e1 = imresize(w1, [128 128]);
r1 = graycomatrix(e1);
disp(r1);
t1 = imhist(e1);
figure, imshow(e1), title('transformed gray Jerry .jpg in gray');
The output will be an 8*8matrix which is a GLCM of input image.
```

A.K-MEANS SEGMENTATION

The k-means algorithm is an evolutionary algorithm that gains its name from its method of operation. The algorithm clusters observations into k groups, where k is provided as an input parameter. It then assigns each observation to clusters based upon the observation's proximity to the mean of the cluster. The cluster's mean is then recomputed and the process begins again. Here's how the algorithm works:

Step 1: The algorithm arbitrarily selects k points as the initial cluster centers ("means").

Step 2: Each point in the dataset is assigned to the closed cluster, based upon the Euclidean distance between each point and each cluster center.

Step 3: Each cluster center is recomputed as the average of the points in that cluster.

Step 4: Step 2 and 3 repeat until the clusters converge. Convergence may be defined differently depending upon the implementation.

Description

Original K-means algorithm choose k points as initial clustering centers, different points may obtain different solutions. In order to diminish the sensitivity of initial point choice, we employ a mediod [I1], which is the most centrally located object in a cluster, to obtain better initial centres. The demand of stochastic sampling is naturally bias the sample to nearly represent the original dataset, that is to say, samples drawn from dataset can't cause distortion and can reflect original data's distribution In order to lessen the influence of sample on choosing initial starting points, following procedures are employed. First, drawing multiple sub-samples (say J) from original dataset (the size of each sub-sample is not more than the capability of the memory, and the sum for the size of J sub-samples is as close as possible to the size of original dataset) . Second, use K-means for each sub-sample and producing a group of medioids respectively. Finally, comparing J solutions and choosing one group having minimal value of square error function as the refined initial points. To avoid dividing one big cluster into two or more ones for adopting square-error criterion, we assume the number of clustering is K' (K >

K, K' depends on the balance of clustering quality and time). In general, bigger K' can expand searching area of solution space, and reduce the situation that there are not any initial values near some extremum. Subsequently, re-clustering the dataset through Kmeans with the chosen initial conditions would produce K' mediods, then merging K' clusters (which are nearest clusters) until the number of clusters reduced to k.

B.FEATURE EXTRACTION USING GLCM

Color Feature

The Color feature is the most general feature extracted from an image. The color images are having the standard Color model known as RGB. Color histogram is a commonly used method for the extraction of color information in CBIR system. Feature refers to the attribute of an object. Feature extraction results in reducing the dimensionality of an object, that form the significant part in image processing.

Gabor filters (wavelet)

For a given image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x, y) = \sum_s \sum_t I(x-s, y-t) \psi_{mn}^*(s, t)$$

where, s and t are the filter mask size variables, and ψ_{mn}^* is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \cdot \exp(j2\pi Wx)$$

Where W is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x, y) = a^{-m} \psi(\tilde{x}, \tilde{y})$$

Where m and n specify the scale and orientation of the wavelet respectively, with $m = 0, 1, \dots, M-1$, $n = 0, 1, \dots, N-1$, and

$$\tilde{x} = a^{-m} (x \cos \theta + y \sin \theta)$$

$$\tilde{y} = a^{-m} (-x \sin \theta + y \cos \theta)$$

Where $a > 1$ and $\theta = n\pi/N$. The variables in the above equations are defined as follows:

$$a = (U_h/U_l)^{\frac{1}{M-1}},$$

$$W_{m,n} = a^m U_l$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m (a-1)U_l},$$

$$\sigma_{y,m,n} = \frac{1}{2\pi \tan\left(\frac{\pi}{2N}\right) \sqrt{2\ln 2 - \left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}}$$

Texture representation

After applying Gabor filters on the image with different orientation at different scale, we obtain an array of magnitudes:

$$E(m, n) = \sum \sum |G_{mn}(x, y)|,$$

$m = 0, 1, \dots, M-1$; $n = 0, 1, \dots, N-1$ These magnitudes represent the energy content at different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture, therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region:

$$\mu_{mn} = \frac{E(m, n)}{P \times Q}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|G_{mn}(x, y)| - \mu_{mn})^2}}{P \times Q}$$

A feature vector f (texture representation) is created using μ_{mn} and σ_{mn} as the feature components [5, 10]. Five scales and 6 orientations are used in common implementation and the feature vector is given by:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \dots, \mu_{45}, \sigma_{45}).$$

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C. CLASSIFICATION USING FEED FORWARD NEURAL NETWORK

Neural Network Characteristics

The word network in Neural Network refers to the interconnection between neurons present in various layers of a system. Every system is basically a 3 layered system, which are Input layer, Hidden Layer and Output Layer. The input layer has input neurons which transfer data via synapses to the hidden layer, and similarly the hidden layer transfers this data to the output layer via more synapses.

Neural Network (NN) can be represented using a directed graph G , an ordered 2-tuple (V, E) consisting of a set V of vertices and E of edges with vertices $V = \{1, 2, n\}$ and arcs $A = \{i \rightarrow j, j \leftarrow i\}$, having the following restrictions:

- V is partitioned into a set of input nodes V_I , hidden nodes, V_H , and output Nodes V_O .
- The vertices are also partitioned into layers.
- Any arc must have node i in layer $h-1$ and node j in layer h .
- Arc is labeled with a numeric value w_{ij} .
- Node i is labeled with a function f_i .

When each edge is assigned an orientation, the graph is directed and is called a directed graph or a diagraph. A feed forward network has directed acyclic graph. Diagraphs are important in neural network theory since signals in NN systems are restricted to flow in particular directions. The vertices of the graph represent neurons

(input/output) and the edges, the synaptic links. The edges are labeled by the weights attached to the synaptic links.

Neural networks essentially comprise three pieces: the architecture or model; the learning algorithm; and the activation functions. Neural networks are programmed or “trained” to “. . . store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; to control ill-defined problems; in summary, to estimate sampled functions when we do not know the form of the functions.” It is precisely these two abilities (pattern recognition and function estimation) which make artificial neural networks (ANN) so prevalent a utility in data mining. As data sets grow to massive sizes, the need for automated processing becomes clear. With their “model-free” estimators and their dual nature, neural networks serve data mining in a myriad of ways.

IV.RESULT

A. INPUT

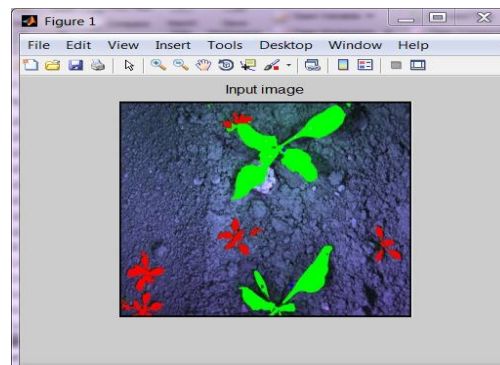


Figure 2: Input Image

B.SEGMENTATION

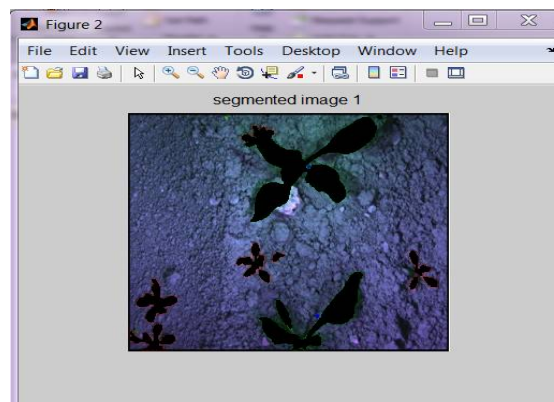


Figure 3: Segmented Image 1

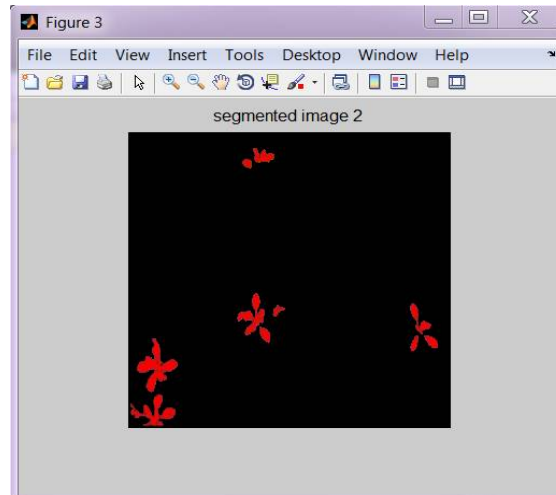


Figure 4: Segmented Image 2

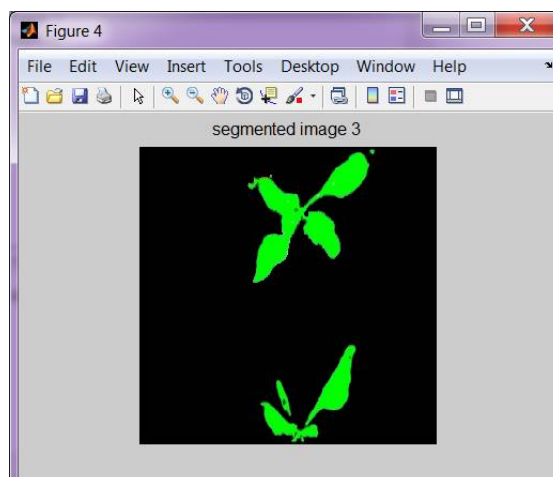


Figure 5: Segmented Image 3

C.FEATURE EXTRACTION

```
Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.

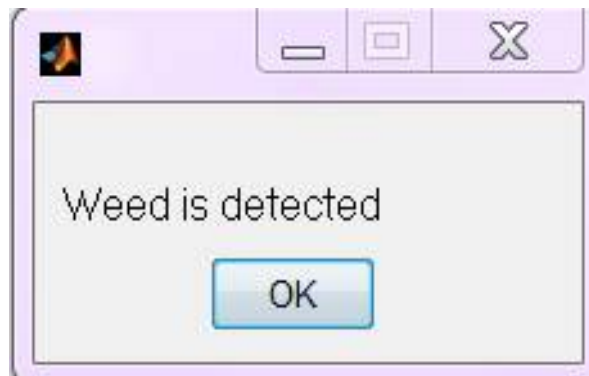
cfeat =
    26.9055

out =
    9.9802

fx >> |
```

Figure 6: Extracted Value

D. CLASSIFICATION USING FEED FORWARD NEURAL NETWORK



E. OUTPUT

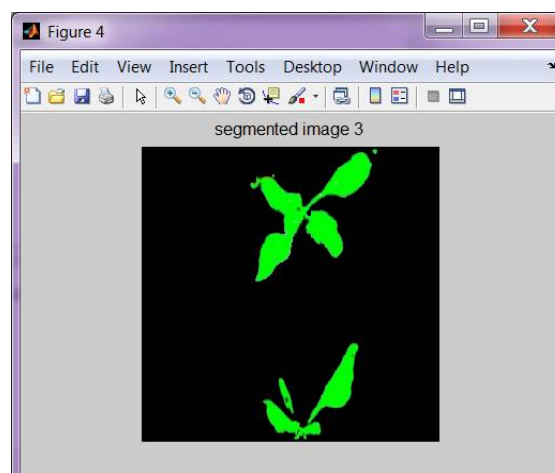


Figure 7: Output Image

V. CONCLUSION

The Gray Level Co-occurrence Matrix (GLCM) method is used for extracting four Statistical Texture Parameters i.e., Entropy, Inverse Difference Moment, Angular Second Moment and Correlation. By extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other DWT Techniques, but however DWT is versatile method of compressing video as a whole. These features are useful in motion estimation of videos and in real time pattern recognition applications like Military & Medical Applications.

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