Vegetation of Low Cost Remote Sensing Images by Mean Shift Algorithm

S.Chitra, R.Subash, C.Premalatha

Abstract— **In recent years, low-cost remote sensing system is developed for small agriculture business. It forms a rapidly developing area of research in remote sensing and relatively low cost and ease of use of this system make it a technology that is readily available for developing countries to gather information. This approach is applied with low-cost digital cameras which emphasis to actual field conditions with variations in illumination, shading and other elements that degrade the image processing techniques. In this paper, we proposed a work that investigates the combination of vegetation in-dices and the mean-shift algorithm, based on the density estimation in the color feature on images taken by a low-cost system. The aim is to segment green coverage area, gaps like soil area and determination of degraded areas. The combination of mean shift algorithm and vegetation indices give better segmentation performance and efficiency when compared with other segmentation methods. The work extend with yield estimation of crop field, weed detection in green coverage area and soil type determination. The images may taken in different field conditions with illumination variation and area of imbalanced sizes.**

keywords— **Image segmentation, precision agriculture, vegetation indices, yield estimation , weed detection.**

I. INTRODUCTION

To manage plantation precision agriculture can help small farmers. Low cost Remote sensing imagery is the most important technologies in this context. However satellite remote sensing images can be expensive, while sub-orbital images are acquired from low-cost systems that can benefit developing countries and small properties [1].

Martins et al. [2] proposed a low-cost remote sensing system based on an image acquisition equipment attached to a helium balloon. The sub-orbital images are acquired by this system that can be transmitted via radio frequency or processed online. The height control (approximately 10 to 100 meters), the need of few persons to operate, and the low cost are the advantages of this low cost remote sensing system. The limitation in regions with trees and electric wires, a low load capability (from 2 to 4 kg) and images taken in same settings are the disadvantages of this system .

The images taken from the low cost system with uncalibrated camera have illumination variation, shadows and other elements that can degrade the automatic image processing analysis. Due to this reason, unsupervised method finds difficult to improve the results based on threshold and vegetation indices. Also, availability of many regions of soil, weed, gaps and degraded areas than region of green coverage samples, the supervised methods also not perform well.

The extraction of green coverage region from the image is one of the most relevant information for analysis. Yield estimation and weed control are performed by accessing a map of green coverage. To perform this task, previous studies proposes method based on threshold Otsu's method [3], histograms and vegetation indices. Vegetation indices such as color index of vegetation extraction (CIVE) [4] , excess green (ExG) [5] and visual vegetation index (VVI) were also proposed, among others, for this purpose. A combination of vegetation indices and MS segmentation [6] improves the segmentation accuracy from the previous results.

For rice orchard management, Crop yield estimation [7] is an important task. The manual sampling-based yield estimation is time-consuming process, labor-intensive and inaccurate also. For end-of-season, Yield estimation is a very important observation. Remote sensing approaches can provide yield estimation by segmentation, gray scale labeling and thresholding to identify the grain and area estimation shows the final estimation across fields. Weeds represent a large management cost which compete with crops for water, nutrients, and light, often reducing crop yield and quality. This paper also describes the classification of soils based on there color and morphological feature.

The aim of this study is to present the unsupervised segmentation of images obtained by the low cost remote sensing system, offering estimation of yield, detection of weed and determination of soil type for planning of precision agriculture. Section II describes the various methods, including the low-cost remote sensing system to acquire the image, three types of vegetation indices, the Mean Shift algorithm, yield estimation, weed detection [8], soil classification [9] and its evaluation. Section III presents result and the concluding remarks in Section IV.

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II. METHODS

A. low cost balloon based remote sensing photo technique

The low cost images taken from the system built with the highly efficient amateur aerial balloon photo technique which takes the photos affordable price approximately 0.25 US cent per hectare. It provides an inexpensive color photos on a high pixel resolution with quality efficient solution. This modern technique is based on a simple plastic balloon, inflated with hydrogen gas, chemically produced and adapted to the field conditions in developing countries for areas with rapid land use changes. In Cambodia, it is offered by a private geospatial company for remote sensing photo technique. The images obtained are resampled to 512×512 pixels, resulting in an approximate resolution of 3.7 cm/pixel.

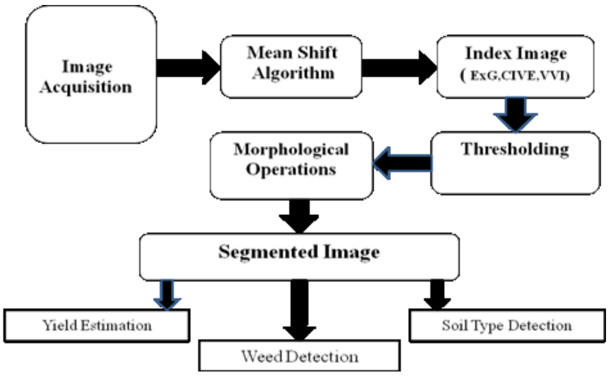

Fig. 1 Architecture of proposed system

B. *Mean Shift Clustering*

Mean shift algorithm is a simple iterative procedure which shifts each data point to the average of data points in its neighborhood. It is later generalized with the inclusion of a kernel function. This generalization makes the k-means like clustering algorithms its special cases. It also shown that the mean shift is a mode-seeking process on which a surface is constructed with a "shadow" kernel. For mean shift iterations convergence is studied. Finding a fixed point of mean shift which characterizes the data is treated as a cluster analysis.

Decomposition of gray level or color image into homogeneous is Image Segmentation. Homogeneity is defined as similarity in pixel values. So the diversity of image segmentation method is proposed. Mean shift is mainly used to find local maxima in the given input image, which removes texture and small irregularities present in the image. Segmentation is done by representing each pixel by its color in a feature space as an empirical probability density function. If the input is a set of points then Mean shift considers them as sampled from the underlying probability density function. If dense regions (or clusters) are present in the feature space , then they correspond to the mode (or local maxima) of the probability density function. For each data point, Mean shift associates it with the nearby peak of the data set's probability density function. For each data point, Mean shift defines a window around it and computes the mean of the data point . Then it shifts the center of the window to the mean and repeats the algorithm till it converges. After each iteration, we can consider that the window shifts to a more denser region of the data set.

C. Vegetation Indices

For extracting the green plant Vegetation indices (VIs) provide a very simple yet elegant method. This technique does some arithmetic operations on the visible lights, near infrared, etc. These indices are mainly used to enhance green color feature information in the images to separate the green plant coverage portion from the background namely, the soil. It visualizes the better vegetation with better contrast in the available bands. Three of the most used indices are CIVE, ExG and VVI .

1. ExG

When visible light is available, the excess green index (ExG) method is used. The ExG method is one of the most famous contrast index the image using the R,G and B chromatic coordinates. It is defined as:

$$ExG = 2g - r - b, \text{ with } r + g + b = 1 \qquad \ldots\ldots\ldots (2.1)$$

where r,g and b are normalized by color=R+G+B

$$r = \frac{R}{color} \qquad g = \frac{G}{color} \qquad b = \frac{B}{color}$$

where R, G and B are the normalized RGB coordinates ranging from 0 to 1.But the normalized green channel was used .

2. CIVE

The CIVE (Color Index of Vegetation Extraction) is computed by

$$Z = 0.441r - 0.811g + 0.385\,b, \qquad \ldots\ldots\ldots (2.2)$$

where r,g and b are normalized by color=R+G+B

$$r = \frac{R}{color} \qquad g = \frac{G}{color} \qquad b = \frac{B}{color}$$

R, G, and B were the values of the RGB intensity of each pixel of image. Using the CIVE, the segmented images of the green plants were easily converted from the color image.

3. VVI

The amount of vegetation or greenness of an image is measured by Visible Vegetation Index (VVI) by using the information from the visible spectrum. To distinguish and separate the vegetation from soil surfaces, information in the near infrared is necessary in imagery. The VVI is an antries to use only information in the visible spectrum and measures the amount of green in a region using similarity indices.

The VVI is given by

$$VVI = \left[\left(1 - \left|\frac{R - R_o}{R + R_o}\right|\right)\left(1 - \left|\frac{G - G_o}{G + G_o}\right|\right)\left(1 - \left|\frac{B - B_o}{B + B_o}\right|\right)\right]^{1/w} \quad \ldots\ldots\ldots(2.3)$$

where R, G, and B are the red, green, and blue components of the image, respectively, RGBo is vector of the reference green color, and w is a weight exponent to adjust the sensitivity of the scale. After various color calibrated image analysis, we found that RGBo = [30, 50, 0] that works well for 24-bit images (256 colors per channel), and w = 1. It is also necessary to add some amount to both the RGB channels and the RGBo to avoid a division by zero in the equation. To measure the amount of global vegetation in the images, the VVI will be used which gives quick results.

D. Otsu segmentation

The Otsu's threshold is applied to resulting image to obtain two interest regions. Otsu's method is used to perform clustering-based image thresholding automatically, or the conversion of a gray level image to a binary image. The algorithm assumes that the image to be threshold contains two classes of pixels(e.g. foreground and background) then calculates the optimum threshold separating those two classes. So their combined spread (intra-class variance) is minimal. This method does not depend on the probability density functions of an image. This method identifies the threshold that maximizes the distinctiveness of the two classes to which it divides the image. This distinctiveness represents the interclass variance.

E. Morphology

The morphology operation here is to neutralize the negative area of the resulting binary image. In a morphological operation, the output image pixel value is compared with the corresponding input image pixel with its neighbours. To construct a morphological operation ,the size and shape of the neighbourhood is choosed that is sensitive to specific shapes in the input image. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.

F. Yield estimation

Predicting rice yield around the panicle initiation stage would provide valuable information for future planning and yield expectations. To estimate total biomass for rice crops to estimate, the Mean Shift and k means clustering algorithms are robust requires no atmospheric corrections and reduces the impact of sunlight intensity variations. Gray scale labeling is done in clustering images to identify the grain. Thresholding is done depending upon the grain color value in feature space on images. Rice crop area has been estimated from images for wide scale yield prediction. Finally rice yield was estimated in ton-per hectare area.

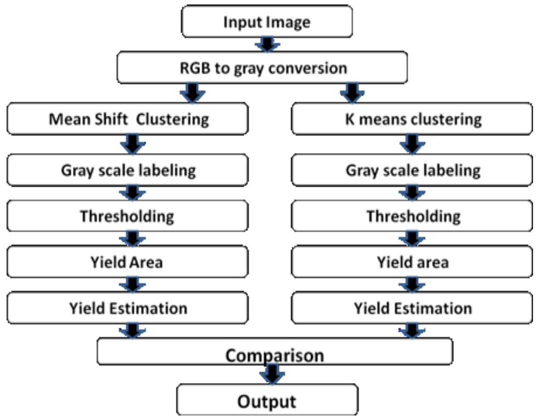

Fig. 2 Architecture of yield estimation

G. Weed detection

Weed is a major menace in crop production as it competes with crops for nutrients, moisture, space and light which resulting in poor growth and development of the crop and finally yield. Machine vision system, remote sensing and aerial imaging techniques are used for weeds control. Almost all the existing weed detection methods process the captured image by segmentation of vegetation against background (soil), detection of weed vegetation pixels. Further, classification of feature extraction of weeds is done by color, shape and texture. Almost all existing weed detection methods process the image based on the following steps [7] such as segmentation of vegetation against the background (soil and/or harvest residues), Detection of the vegetation pixels that represent weeds and feature extraction and classification.

H. Soil type detection

The soils are classified based on the color and boundary features. Boundary feature include area, equidiameter. The work involves processing the images of different types of soil (like red soil, black soil, black cotton soil etc) , by extracting the features. The idea is to classify different types of soils using color and morphological features. Algorithms are developed to acquire and process color images of soil samples. Different types of soil are considered like red, and black etc. The algorithms are used to extract 18 color, and three other features.

I. Evaluation

The images labeled were used as the ground truth. We used a repeated random sub-sampling validation, each experiment was repeated several times. The average and standard deviation were computed by these repetitions. The evaluation was based on the balanced accuracy value that takes into account the balance between the regions.

The accuracy is calculated by

r

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$$Acc = 1 - \frac{\sum_{I=1} [e_{i,1} + e_{i,2}]}{2r}, \quad \ldots\ldots\ldots (3.4)$$

$$\mathbf{e_{i,1}} = \frac{FP(i)}{N - N(i)}, \quad e_{i,2} = \frac{FN(i)}{N(i)}, \quad i=1\ldots\ldots r$$

where r is the number of regions, [ei;1 + ei;2] is the partial error of the region i, FN(i) (false negatives) is the number of samples belonging to i incorrectly classified as belonging to other regions, and FP(i) (false positives) the samples $j \neq i$ that were assigned to I .

III RESULTS AND DISCUSSION

The average accuracies and standard deviation for the segmented images by various combination of vegetation indices methods and MS algorithm are presented in Table I. The MS with vegetation indices methods showed accuracies better than the previously proposed segmentation methods.

Table 1. Average accuracy and standard deviation for 10 images

Methods	$x \pm SD$
MS+CIVE	84.2 ± 5.2
MS+ExG	85.0± 6.4
MS+VVI	71.6±13.3

The unsupervised methods based on vegetation indices, MS-ExG, performed well, with results comparable with the other methods

IV. CONCLUSION

This work report results of an MS with vegetation indices methods applied to the green coverage detection problem. The isolated use of vegetation indices often oversegments the images, producing nonuniform regions. Besides, this approach carries most advantages of unsupervised algorithms, such as the incremental capability, in which new samples can be easily added to the model.

Among the investigated various vegetation indices methods, the ExG index showed best results, since CIVE and VVI produced lower accuracies and unstable results when dealing with different images showing higher variance. When computed over the previously segmented image, both CIVE and ExG showed good results. The VVI could not be improved by using an MS segmentation. The MS + CIVE and MS + ExG methods are unsupervised and fast to compute.

Low cost remote sensing system was used to acquire images over a rice canopy to estimate rice yield. Rice yield and total biomass were found to be significantly different at the 0.05 and 0.1 significance levels, respectively, under different N treatment regimes.

It could be concluded from the weed detection by color space methods are used for foreground and background extraction. With the numerous amounts of crop and weed segmentation techniques presented above. The color space RGB planes with coefficients (r = -0.884, g = 1.262, b = -0.311), mean pixel intensity thresholding and Robust Crop Row Detection system successfully detects an average of 95 % of weeds and 80 % of crops under different illumination, soil humidity and weed/crop growth conditions.

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AUTHOR(S) PROFILE

Mrs. Chitra.S, Pursuing Master of Engineering in Ranganathan Engineering College, Affiliated to Anna University, Chennai. Received her B.Tech degree in computer science from NIT, Trichy. Currently working on a project in An efficient Segmentation of low cost images and its applications. Her research interests include Image processing,Data Mining.

Mr. Subash.R completed his B.Tech(IT) from national college of Engg.,Tirunelveli and M.E(CSE) from Dr.Sivanthi Adithanai college of Engg,Tiruchendur. Currently, working as Assistant Professor in the Department of Computer Science and Engineering at Ranganathan Engineering College ,Coimbatore,Tamil Nadu, India. His research interests include Data Mining, image processing

Ms Premalatha.C Pursuing Master of Engineering in Ranganathan Engineering College, Affiliated to Anna University, Chennai. Received her B.Tech degree in Information Technology from Sri Ramakrishna Engineering college,Coimbatore respectively. Her research interests are knowledge discovery and data mining, green computing, security of internet and intranet.

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