eAGROBOT- A Robot for Early Crop Disease Detection using Image Processing

Sai Kirthi Pilli[1], Bharathiraja Nallathambi, Smith Jessy George, Vivek Diwanji

[1]*Engineering and Manufacturing Solutions Business Unit ,Cognizant Technology Solutions, Hyderabad, India*

sai.pilli@cognizant.com

Abstract— **Management of crops from early stage to mature harvest stage involves identification and monitoring of plant diseases, nutrient deficiency, controlled irrigation and controlled use of fertilizers and pesticides. Although the number of remote sensing solutions is increasing, the availability and ground visibility during critical growth stages of crops continue to be major concerns. eAGROBOT (a prototype) is a ground based agricultural robot that overcomes challenges existing in large and complex satellite based solutions and helpdesk form of solutions available as m-Services. It provides a small, portable and reliable platform to automatically survey farmland, detect diseases as well as spray the pesticide. In future, the farmer can obtain a consolidated view of the farm along with decision support statistics for planning purposes. The development of eAGROBOT, real time testing results obtained from cotton and groundnut plantations and future focus has been detailed in this paper.**

Keywords: ***Agricultural robot; pest identification, Image processing***

I. INTRODUCTION

Precision crop management (PCM) is well adopted in developed countries and known to improve crop yield, optimize use of chemicals and fertilizer, reduce costs and pollution as well as enable better management. Image based solutions are particularly well suited for remote sensing applications, and can meet the accuracy, resolution and timeliness requirements of typical PCM applications [1]. In addition, geospatial applications enable data and information related to geography and space to be managed, processed, and visualized.

Today, satellite based imaging solutions such as the SIBWA [2], Quick Bird [3] are gaining popularity in places including West Africa and Germany. SIBWA uses Very High Resolution Imagery (VHRI) of land and enhances the image to estimate variations of soil fertility, land size and shape while Quick Bird collects reflectance data 450 km above. The spatial and temporal resolution can be better for image acquisition done using an aircraft. The basic principles of remote sensing with satellites and aircrafts are similar, i.e., interpreting the reflectance values at various wavelengths (visible and infrared regions) of the electromagnetic spectrum. Large amount of processing is done which includes ortho rectification, pan sharpening with image data fusion, enhancements, geo-referencing, mosaicking, color/grayscale balancing and implementation into a mapping environment such as GIS (Geographic Information Systems). There however, still exist number of challenges in terms of calibration, geometric correction, cost (a single VHRI image costs between US$ 1000-1500 [4]), environmental issues (cloud interference), turnaround time and repeat frequency of these remote solutions.

On the other hand, mobile services (mKrishi, Nokia Life tools, IFFCO Kisan Sanchar Limited [2]) are gaining popularity in India for providing agricultural extension, social connectivity and financial support. These are well suited for query resolution, information on markets and upload of static image type of applications. Tele- centers (e-sagu, farmer help lines [2] also depend on automation of query resolution using databases or depend on experts for query resolution.

Sensors located in fields along with hand-held or tractor based solutions on the other hand provide the missing link [5]. Such devices can be used for very high spatial resolution and by consolidation of results, can also be used for providing information of a larger farmland. Such a solution becomes especially important for parameters such as soil nitrate and soil moisture, which can change rapidly (both spatially and temporally) and must be measured in real-time or near real-time to be useful for input control. The eAGROBOT presented here is an autonomous field robot tested extensively in cotton as well as groundnut fields using different experimental image sizes with resolutions of 640x480 pixels and 1024x768 pixels. Large resolution is used for wide images and the results have been demonstrated. The robot helps the farmer to take informed decision locally or allows connecting with other existing services (for example, upload the pictures for expert opinion). Ordinary camera (webcam, mobile camera) is deployed in this study, to bring down the cost of the overall solution.

II. AGRICULTURAL SETUP IN INDIA

Today, a large percentage of farmers in India use pesticides with maximum use in cash crops such as cotton, sugarcane or vegetables (Fig. 1).

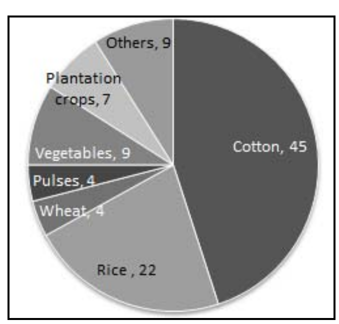

Fig. 1. Pesticide consumption in India by different crops

However, in more than 40% cases, it is found that farmers use an overdose of pesticides (1.5 to 20 times the prescribed dose) [6, 7]. Even a 75% accuracy in measurements [1] of most crop and soil conditions has potential in improving farm profits considering that more than 40% overdose cases have been reported in surveys for pesticides

A Challenges faced by farmers

Plant diseases can cause significant reduction in both quality and quantity of agricultural products [8]. Typically different types of diseases are seen at different stages of development of the crops. The rate of spread differs and so does the type of pesticide. Visual inspection is the main approach adopted in practice for detection and identification of plant diseases [8]. However, this requires continuous monitoring by experts which might be prohibitively expensive. Further, in some cases, farmers may have to travel long distance to contact experts, this makes consulting experts too expensive and time consuming [9; 10; 11]. Therefore, quick, automatic, less expensive but accurate method to detect plant disease cases is of great practical significance [9; 10].

B Current Practices

During a survey conducted by authors among the farmers growing groundnut at Salem, TamilNadu, India, it is found that, they conduct routine visual survey of their farmland; they are aware of the more common diseases and seek help of nearby knowledgeable farmers or approach dealers with a sample of infected crop if in case of doubt. For groundnut farms, different pesticides with chemicals such as carbendazim, chlorothalonil, mancozeb are used during different stages of crop lifecycle. Even then, once in three years, some farmers face extensive crop damage, the main reason being novel diseases and delay in getting critical information about controlling the spread (diseases such as Aspergillus crown rot, Rust, Bud necrosis can spread over acres in a matter of weeks). Over the years farmers have been using helplines setup by government, such as the TamilNadu Agriculture University Portal, Kisan Call Centre, and are also exploring new solutions that leverage emerging imaging and M2M technologies;. Typically, the farmers mostly borrow farming equipment such as tractors and mechanical sprayers. The satellite based solutions can indicate the presence of disease (detection of disease type is more challenging), if the spread is limited to 1 acre. Agriculture departments under Government of India on the other hand plan to take corrective action when a considerable mass of land (5 to 8 acres) is found infected. In contrast, small-holder farmers use pesticides when less than 1/3rd of an acre is infected.

III. Opportunity for Image based solutions

Both visible and infrared regions of the electromagnetic spectra are used extensively to detect and diagnose defects in crop as well as soil. Studies show that machine learning methods can successfully be applied as an effective early disease detection mechanism [10, 11, 12, 13, 14, 15, 16, and 17]. Examples of such machine learning methods that have been applied in agricultural researches include Artificial Neural Networks (ANNs), Decision Trees, K-means, k-nearest neighbors, and Support Vector Machines (SVMs).

In [14] Bauer et al have worked on the development of methods for the automatic classification of plant diseases based on high resolution multispectral and stereo images. In [8], a fast and accurate new method is developed based on computer image processing for grading of plant diseases. Approach uses segmentation using Otsu method and Sobel operator to detect the disease spot edges and gradation by calculating the quotient of disease spot and plant areas. Wang et al. in [16] predicted Phytophthorainfestans on tomatoes by using ANNs. Also, Camargo and Smith [10] used SVMs to identify visual symptoms of cotton diseases using SVMs. H. Al-Hiary et al [17] proposed method based on application of K-means as a clustering procedure and ANNs as a classifier tool [13] in terms of speed of computation and accuracy. Two steps are added; one in which green colored pixels are identified for masking and second where pixels with zeros red, green and blue values together with the pixels on the boundaries of the infected cluster are completely removed.

Some solutions are also available in the microscopic to telescopic range, such as the ColorPro software for estimation of infected leaf area, chlorophyll, protein, and bacterial colonies count; CytoPro for chromosome analysis and others by BARC [18]. This has manifested confidence in image based solutions similar to the satellite solutions.

IV. E-AGROBOT

A Schematic of eAGROBOT

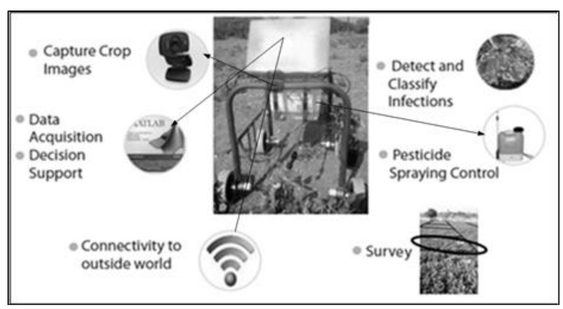

Fig. 2. Schematic diagram of eAGROBOT

The functional components of eAGROBOT, shown in Fig. 2, include a camera that captures pictures of the plant, AI based embedded algorithms that pick regions of interest and perform color transformations to identify type and extend of diseases, the sprayer mechanism that sprays the requisite pesticide, and has Wi-Fi connectivity for necessary expert support. The robot itself can move automatically on a farmland according to specified maneuvers or can be controlled remotely.

B eAGROBOT Design Considerations

The robot has been designed and built considering design constraints such as lightweight frame structure, undulating field surfaces, compact sizing (sufficient enough to hold all components- the processing boards, battery, camera and a 8L pesticide can) and portability(doing minimum damage to the crops during traversal). Additional space for laptop and accessories such as extra camera etc. has been built-in for real time testing to be conducted. Image processing algorithms have been designed to handle issues such as sunlight and dim light effect. Most of these challenges, except the background rejection (or influence of soil in background) are addressed today. The robot is tested in groundnut plantations to evaluate its real time performance. Going forward, challenges such as detection of flower/fruit and its influence in the decision support will also be addressed.

C Image processing

The authors used the approach by Al-Hiary et al [17] for building disease detection capability of eAGROBOT. The basic steps, involve image acquisition, pre-processing, segmentation, feature extraction, statistical analysis and classification. This solution is further enhanced with added image pre-processing capability such as detection of blur, color balancing and haze in the captured image.

The sequence of steps followed is shown in Fig. 3. The RGB (Red-Green-Blue) image obtained is preprocessed for color balance, blur, etc. The image is then transformed and clustered to detect the cluster image of interest. After masking of green pixels, the image is converted from RGB to HSV (Hue-Saturation-Value) color space for computation of textual features. These selective features (table 1) then form the input to the Neural Networks program which can detect and diagnose the disease (output of NN is 1 or 0, which indicates presence of disease). This decision leads to the pesticide spray action.

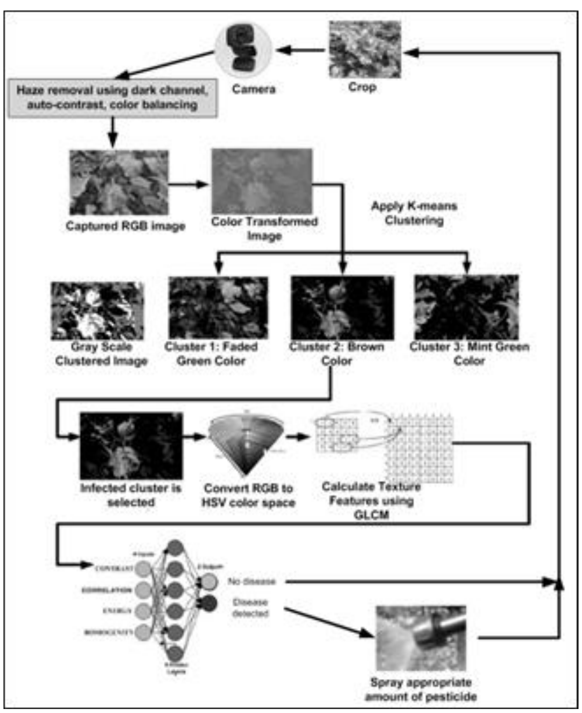

Fig. 3. Flowchart of algorithm steps following in image processing

All the algorithm steps are run for each type of crop. The number of nodes in k-means clustering step and number of nodes of Neural Network, single hidden layer using back propagation technique are varied with the number and type of diseases. However in both cases eight textual features are used. The features set shown in Table 1 are computed for the components hue and saturation.

TABLE I. FEATURE SET

Feature	Detail
Contrast	Measures the local variations in the gray-level co-occurrence matrix
Correlation	Measures the joint probability occurrence of the specified pixel pairs
Energy	Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal

D Experimental Setup

Data acquisition is done from cotton plantations at Vattinagulapally village, near Gandipet, Hyderabad and groundnut plantations at Salem. Data was acquired during, June 2012 for cotton crops (Square to Flower stage) and the climatic conditions were 380C (100F) hot and humid. And for the groundnut crops (Pegging stage), it was in mid of Jan 2013, 320C (90F) clear sky. Authors have chosen cotton and groundnut in particular since these are cash crop with high economic value and are also large consumers of pesticides.

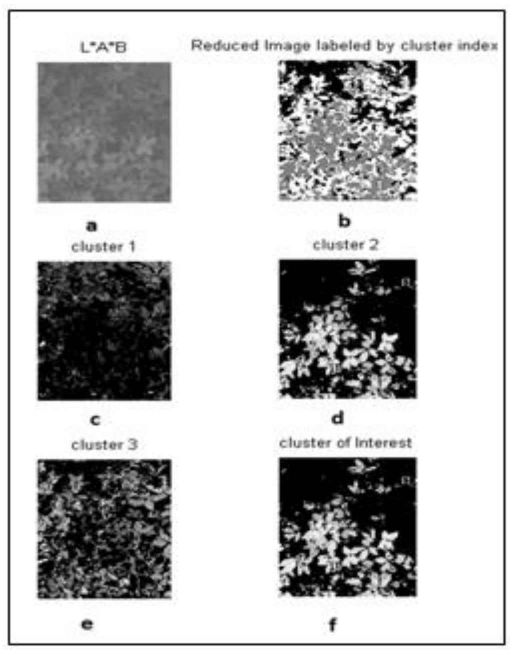

Fig. 4. An example of the output of K-Means clustering for a groundnut plants that is infected with Anthracnose disease [a] The captured image [c; d; e] the pixels of the first, second, the third clusters [b] A single gray-scale image with the cluster index

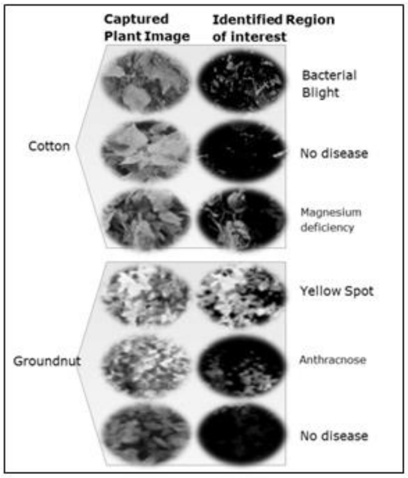

Fig. 5. Identified cluster for different images in cotton and groundnut.

A grid-wise approach is considered for data acquisition as well as for testing. The grids with average size of 5mX3m are based on the physical separation of farms (done for irrigation). Two different sizes of images are considered, i.e. 1mX1m called as wide and 0.5mX0.5m called here as normal. Fig. 4 shows the results of k-means clustering for a sample image of groundnut farm.

Fig. 5 shows the region of interest (or selected cluster) for a number of sample images for both cotton and groundnut plantations.

The Pearson's r and p-values which give crude estimates of correlations between textual features and the type of disease is presented in Table 2. The 'correlation of hue' and 'correlation of saturation' show strong negative relationships. Most features show weak to moderate relationships, except 'homogeneity of saturation'; where the correlation is shown to be non-significant. However all features are used for diagnosis of disease.

TABLE II. PEARSON'S R AND P-VALUES

Area of interest	Parameter	Contrast of Hue	Correlation of Hue	Energy of Hue	Homogeneity of Hue
1mx1m	Pearson's r-value	0.3935	-0.5367	-0.3107	-0.3451
	Pearson's p-value	0.0025	0	0.0187	0.0086
0.5mx0.5m	Pearson's r-value	0.1858	-0.5078	0.4745	0.2013
	Pearson's p-value	0.0081	0	0	0.0041
1mx1m	Pearson's r-value	0.3471	-0.8043	-0.2589	-0.1203
	Pearson's p-value	0.0082	0	0.0518	0.3729
0.5mx0.5m	Pearson's r-value	0.242	-0.634	0.3208	-0.0575
	Pearson's p-value	0.0005	0	0	0.4167

E Field trials

For cotton plantations, bacterial blight and magnesium deficiency are used for classification. The test is conducted to study the challenges that need to be addressed during a real time run as well as to have a preliminary estimate of the algorithm accuracy. The groundnut/cotton crop data is a random multiple sample section of the field and is used for the further analysis. An accuracy of 90+ % is obtained for cotton diseases detection.

Real time testing (end to end) is later done on the groundnut plantations. Groundnut crops undergo 11 stages of development starting from emergence (wherein there is no possibility of disease) to beginning pod (rust and bud necrosis), beginning seed (Aspergillus crown rot, Anthracnose), beginning maturity (Stem rot, Kalahasti malady, Alternaria leaf disease), till over mature pod (Anthracnose, Leaf spot - Late Stage). During the testing phase, crops are at the 'beginning seed' stage where diseases like Leaf spot (both early and late) as well as Anthracnose are predominantly found. The results are shown in Fig. 7 and Fig. 8. The accuracy for normal images is 83-96% for disease identification, while for wide images it is 89%.

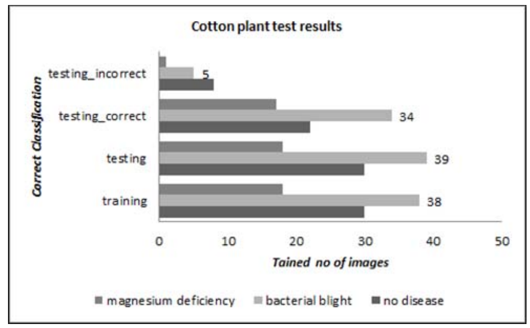

Fig. 6. Distribution and results of testing in cotton plantations

A cross validation is done to verify if images sizes can be changed. As we can see from the Fig. 7 and Fig. 8, the model trained with wider images shows less percentage of incorrect classification even when used for normal images while vice-versa is not true. The 1mx1m size gives better result in this study, however further comparisons with different image sizing is required to find the optimal size and resolution. Results show that eAGROBOT is able to distinguish between early and late leaf spot diseases with good accuracy. The model trained using 1mX1m images gave good results even with smaller images, however the reverse is not true (not included). This cross testing is done to check the sensitivity of accuracy to change in image sizing and resolution.

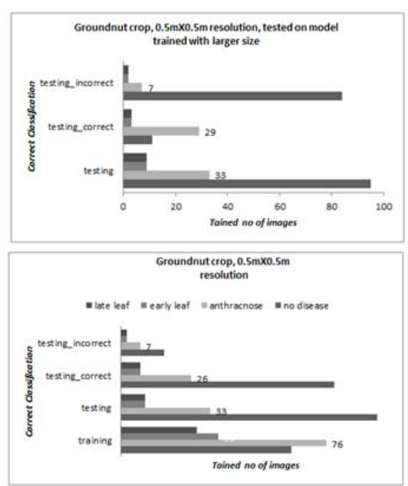

Fig. 7. Distribution and results of testing in groundnut plantations (0.5mX0.5m)

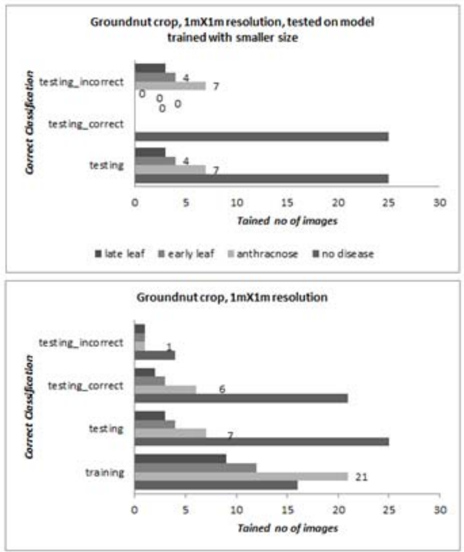

Fig. 8. Distribution and results of testing in groundnut plantations (1mX1m)

An idea for consolidation of images is presented here to help enhance the visualization of whole farm as well as aggregation of data. The embedded program of eAGROBOT is designed such that it can automatically scan a pre-set area. The path for the robot can be set, such that an entire field can be automatically surveyed. An experimental study is done to check if the images captured by the robot can be used for consolidation to that of a larger farm land area. To test this idea, robot is made to traverse through sections in a pre-configured path and pictures taken are stitched together to make up whole sections. A sample of such a stitched section is shown in Fig. 9. Aggregation of image captured and mapping it to larger land area enables further processing in the solution, i.e., information of neighboring grids can be used to improve the accuracy results.

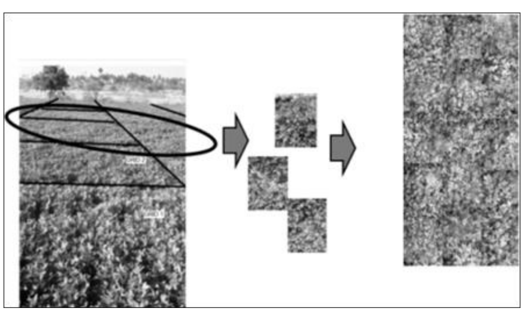

Fig. 9. Slicing of farmland, image capture and stitching by eAGROBOT

Alternatively a camera device connected to tractor can also be used to collect the snaps. This solution also forms a convenient decision support point for the farmer, where a wider farmland view along with recommendations can be made available to the farmer.

Further in an era of connected devices, using m2m, the image processing solution can be made cloud based and support can be made available on smartphones. This will further decrease the cost to end user, enabling integration with subscription based solutions for expert opinion and easy integration and maintenance of image and disease related data repositories.

V. Conclusion

Countries like India or West Africa are dominated by small-holder farmers who work in variable and unpredictable environments. To cater to their needs, a whole gamut of services is needed. Cost effective solutions which have potential to aid the farmers in real time (field based solutions, m-Services) as well as complex solutions (satellite based) that can have a rich content of information are needed. eAGROBOT is built as an autonomous agricultural field robot that works at a micro level (image resolutions higher than 0.01m) and provides users with real time detection of disease along with controlled spraying of pesticide. It can also provide an intelligent consolidation at a macro level, i.e. an entire view of the farmland.

The accuracy levels for disease identification for groundnut and cotton plantations are found to be satisfactory. The consolidation experiment is done manually without GIS information or GPS integration in place; hence its accuracy is not computed.

In future, this solution can be enhanced to a standalone full autonomous form (like BoniRob [19]) or the disease identification features can be integrated to devices such as the tractors. Additionally, integration with central repositories of image information such as the Crop doctor from aAqua [20] can be done to cater to more crops/plant and more diseases. Thus, use of mapping features, cloud computing and m2m will ultimately lead to cost effective solutions for support of the farmers.

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