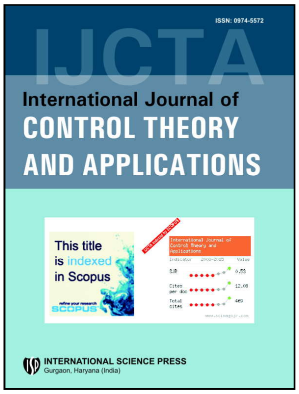

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Pest and Weed detection and application of Pesticide in Agriculture Field using Multicopter

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Abstract: This paper is intended for automatic detection of pest and logging the plants group global coordinates and voluntarily sprays the pesticide in the vicinity for the group of plants. The main parts of this development are: multi-spectral Imaging sub-system and Global Positioning System on Autonomous multicopter and Software package to detect weeds. The infested plant areas, its GPS coordinates for video stream and advice the pesticide to be used and attachment for aautonomous multicopter that sprays the pesticide. A multi spectral imaging with GPS system will be carried out by the multicopter. A GPS guided multicopter fly within the finite geometry and take the image of the entire filed. Various morphological features of specimens' are obtained by special and multispectral image processing tools. The infected group of plants will be spotted out and could apply the pesticide.

Keywords: Spectral Response, Feature extraction, Segmentation, Pesticide, Global Positioning System

1. INTRODUCTION

Timely examination of crop diseases in fields is significant for exactitude on-farm disease regulation. Remote sensing technology can be used as an effectual and economical method to identify diseased plants in a countryside scale[1, 2]. However, due to the miscellany of crops and their allied diseases, relevance of the technology to farming is still in research stage, which desires to be ornately investigated for algorithm enlargement and standard image processing procedures. The application of broadband high spatial resolution Airborne Data Acquisition and Registration (ADAR) was examined by many scientists and remote sensing data to detect rice sheath blight and suggested approaches to further explore the applicability[3, 4]. Based on the field indication capacity, a comprehensive field disease index (DI) was constructed to measure infection severity of the disease and to relate to image sampled infections. The results indicated that the broadband remote sensing imagery has the capability to detect the disease. Some image indices such as RI_{14}, SDI_{14} and SDI_{24} worked better than others. A parallel coefficient over 0.62 indicated that these indexes would be expensive to use for identification of the rice disease[5].

Many scientists have evaluated the potential of multi–spectral [6, 13] airborne remote sensing for the detection of weed infestation in various crops including rice, wheat, corn, soybean, etc. A multi–spectral image in 24 wavebands (475.12 nm to 910.01 nm wavelength range) was used in the experimentation using an airborne platform. Statistical analysis of radiance values recorded in different wavebands was performed to find the wavelength regions that were most useful for detecting unusual weed infestations. The outcome specifies that wavebands centered at 675.98 nm and 685.17 nm in the red area and starting 743.930 nm to 830.430 nm in the near infrared, have good possible for characteristic weeds in corn. For soybean, on the other hand, only one waveband (811.40 nm) was found to be useful.

Presently, two different approaches for weed monitoring and patch spraying are being followed. The primary approach involves the development of weed maps and decision making earlier to the appliance of herbicides. The supplementary approach is based on the real time exposure of weeds and on decision making at the time of spraying. Methods of ground surveying for specific information about weeds are very labor rigorous and time consuming. However, image based remote sensing has potential applications in weed detection for site–specific weed management. The current technology with precision in the field of agriculture and the most promising application is the Remote sensing technology. Currently, however, due to improved resolution and litheness in function, airborne remote sensing is fetching important for time critical and time specific precision crop management[7, 8, 9].

Current research efforts are directed toward assessing its utility for monitoring crop conditions and identifying exact factors harmful to crop yield, including weed infestation. These applications could be easily integrated into precision agricultural practices[10. 11, 12].

The rest of the paper is organized as follows. Proposed methodology is explained in section II. Remote Sensing for Weed Detection is explained in section III Experimental results are presented in section III. Concluding remarks are given in section V.

2. METHODOLOGY

A multicopter will be designed with onboard computing system and the facilities like GPS, balanced Camera with multiple filters, video storage and wireless communication, etc. The field to be imaged will be defined by means of waypoints. The waypoints are nothing but GPS coordinates. The waypoints will be graphically programmable into Multicopter system. The copter flies at the predefined altitude, speed. The altitude will depend on the crop height. On start the copter will fly at the defined height and speed such that it covers all the area within the waypoints bounds. The copter's computer will also register the starting point's GPS coordinates. While flying it captures the video and stores in its own memory. The copter continuously monitors its own battery power. In case the battery is below the danger level, it registers the current GPS coordinates and returns to the base (Starting point) and indicates that as "Low Power". After recharge and as started, it goes to the point where it had left and completes the rest of the field video. While recording the video, the GPS coordinates are also stored such that they become the future reference for the video. Once the imaging is completed, the copter returns to the base. It now analyses the multi spectral video to identify the pest and weed separately. Special multi spectral image algorithms for image processing for various morphological features of specimens will be extracted and analyzed. This analysis will identify the pest/weed along with the appropriate GPS coordinates as shown in Figure-1.

The reference values of size and colour components sampled from many insects for each species will be used accordingly to characterize the species and methods. On selection of pest or weed control as the target job; it will invoke the AI subsystem to suggest the type and quantity of the insecticide as per the data made available in its data base. Now the camera attachment is removed and spraying mechanism with pesticide is attached to the copter. On restart, the copter fly to the GPS coordinates of the identified pest or wand enable the spray. After the spraying on all the identified GPS coordinates, the copter will return to the base point.

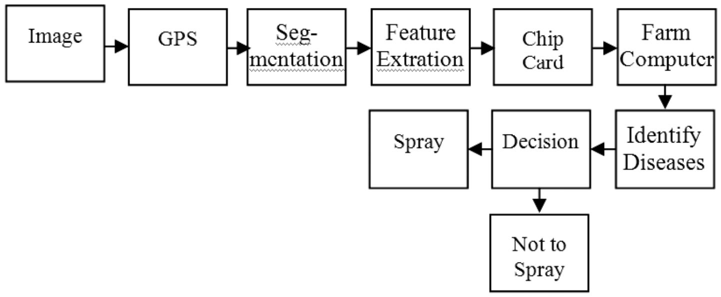

Figure 1: Pest and weed detection process and Pesticide

3. REMOTE SENSING FOR WEED DETECTION

The forest canopy or spectral response of a crop depends mostly on the underlying soil and optical reaction of leaves. However, additional parts of the plants also sway the overall canopy response work on the possible use of spectral properties of plants for the discrimination of crops. If the disparity in the spectral responses in different wavebands of different plants can be measured, pest effected weeds and parts can be discriminated. It is requisite that a major difference among the pests, spectra of weeds and other factors (soil and plant) should exist for the detection of pests and weeds using remote sensing technology. To measure this difference, the remote sensing instruments should consist of appropriate spectral and spatial resolution.

Researchers used aerial photography in conventional color and in color infrared to detect pests and weeds in agricultural and horticultural crops. High–resolution aerial photography was used for collecting information on crop disease, pest infestations, and the presence of weeds and showed that it is possible to distinguish them from crops in different combinations using color infrared photography. The maximum difference between weed populations and the crop was found to be in the near infrared (850 nm) and visible (550 nm) wavelengths. It has been reported that climbing milkweed in orange groves, ragweed in carro fields, Johnson grass and palmer amaranth in cotton and London rocket in cabbage It has been observed that the detection of weeds in crops can be attributed to differences in leaf area, inter-cellular spaces, chlorophyll content and color in the entity leaves. The differences that are mentioned here are not unswerving and were reliant on the crop and weed growth stage.

4. SPECTRAL RESPONSE

Researchers carried out potted experiments of rice (Oryza sativa L.) plants and produced various scales of brown plant hopper and leaf folder infestations respectively. For canopy hyper spectral reflectance capacity, and

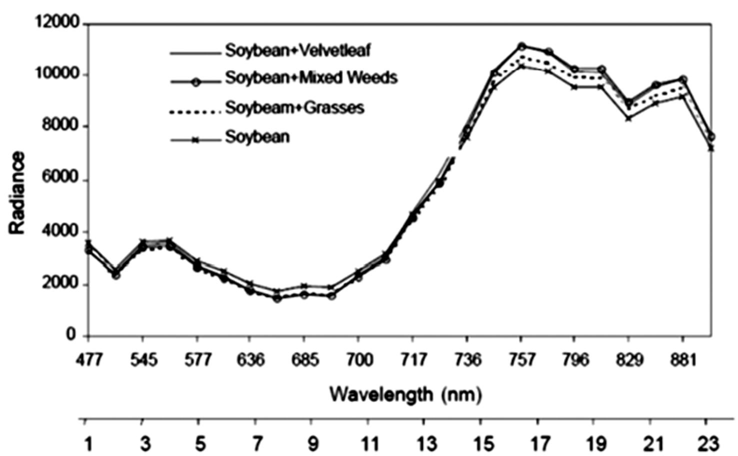

Figure 2: Mean radiance of soybean under different weed treatments indifferent wave bands.

then to make out spectral characteristics (SCs) associated with insect infestations primary to the establishment of spectral models for sternness assessment. By linear intensity correlation analysis, coefficients of correlation (*r*) and the spectral domain of 360 to 2500 nm are detected and narrow bands related to infestation severity are selected as SCs.

The reflectance at green light (490–560 nm) maximum (R_{GREEN}), red light (640–740 nm) minimum (R_{RED}), and near-infrared (740–1300 nm) peak (R_{NIR}) were also considered. For canopies infested with brown plant hopper, *r* value at 426 nm was the highest ($r = 0.878$).

Among the calculated spectral indices using two SCs, the determination coefficient of R_{NIR}/R_{RED} ratio was the highest ($R^2 = 0.922$, $P < 0.001$). For leaf folder diseased canopies, the most unconstructive *r* value located at 757 nm ($r = –0.613*$) in dynamic tillering stage but shifted to 445 nm ($r = –0.928**$) in heading stage.

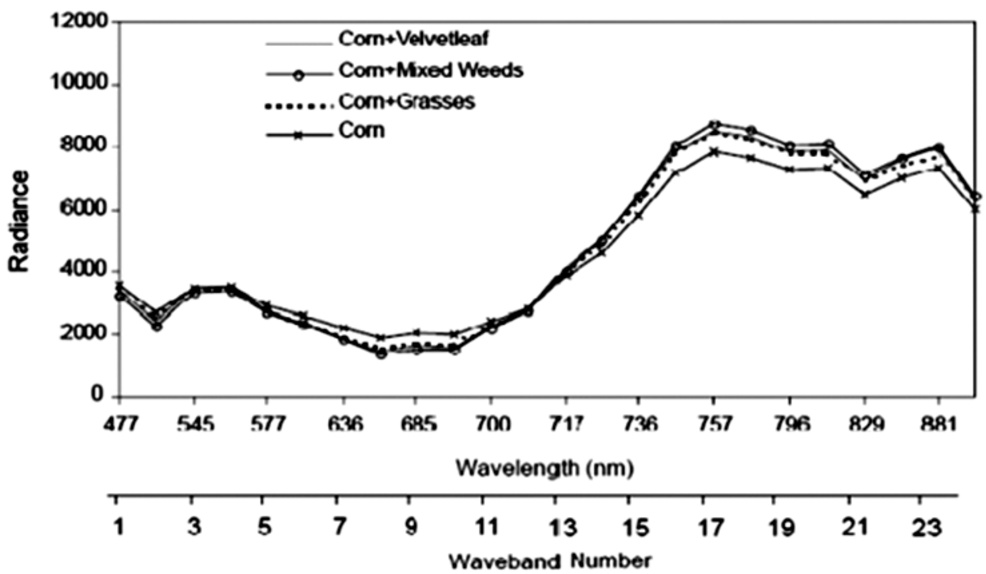

Figure 3: Mean radiance of corn under different weed treatments indifferent wave bands.

The index $R_{NIR} – R_{RED}$ in the active tillering increased R^2 value to 0.422 ($P < 0.001$), while no add to in R^2 was found in the examined SIs in heading stage. Models with more than two spectral characteristics yielded from several linear decay analyses exhibited a further improvement for discriminating huge number sternness. Some of the spectral curves of the different weed infestation treatments as found in literature are illustrated in figure 2 and figure 3 for corn and soybean, respectively. High absorption in the visible bands and high reflectance in the near–infrared bands are typical of undergrowth reflectance curves. The radiance curves of all the treatments were similar in this view. Guyot (1990) has reported that, in the visible domain (400 to 700 nm), leaf reflectance is low (less than 15%) due to high absorption by leaf pigments such as chlorophyll, xanthophyll, cartenoids, and anthocyanins. Since chlorophyll a and b in plant leaves exhibit maximum absorption in the blue and red bands, leaves have maximum reflectance at 550 nm, in the yellow–green region. In the near–infrared region, reflectance of leaves alone could be as high as 50%. However, the reflectance spectra of entire canopies are influenced by combinations of plants and the underlying soil. In all the treatments, the maximum radiance in the visible spectrum was recorded in wavebands centered at 545 and 556 nm (yellow–green region). Higher radiance was recorded in the near–infrared domain.

A helicopter based on radio controlled unmanned low altitude remote sensing (LARS) platform can be used to acquire very high quality images of high spatial and temporal resolution in order to estimate yield and total biomass of a rice crop (Oryza sativa L). Fifteen to sixteen rice field plots along with five N treatments (0, 33, 66, 99, and 132 kg/ha) that have three replicates each are arranged in a randomized complete block design for estimating yield and biomass as a role of functional N. Descriptions were obtained by image gaining sensors mounted on the LARS platform operating at the height of 20 m over new plots. The rice yield and total biomass for the five N treatments were set up to be extensively different at the 0.1 and 0.05 levels of connotation, in that order and NDVI (normalized difference vegetation index) standards at panicle initiation stage are greatly correlated with yield and total biomass with regression coefficients (r2) of 0.729 (RMSE = 0.460 ton/ha) and 0.765 (RMSE = 0.599 ton/ha) respectively. The study verified the correctness of with LARS images as a substitute for satellite images for estimating chlorophyll in leaf content in terms of all NDVI values (RMSE = 0.012 and r2 = 0.897). The LARS system that described here has potential to evaluate areas that require additional nutrients at critical growth stages to improve final yield in rice cropping.

5. CONCLUSION

The proposed method have far reaching applications for many sectors, but the important focus is on applications for the agriculture fields. The growth is aimed mainly for pest and weed control for agricultural crops of huge areas. The advance of multicopter could help acquiring the images and video of any kind of crop. Nevertheless modifications can be included in the pest and weed recognition part of the software package for each kind of crop where the pest and weed may be dissimilar for dissimilar crops. Hence it gives raise to numerous applications in this agriculture sector.

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