Determination of Green Leaves Density Using Normalized Difference Vegetation Index via Image Processing of In-Field Drone-Captured Image

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***Abstract*—Normalized Difference Vegetation Index (NDVI) is a technique which utilizes the near-infrared and visible bands of the electromagnetic spectrum in order to quantify the vegetation density in a specific area. This study presents a method to determine the NDVI levels of a certain rice paddy through the use of images captured using unmanned aerial vehicle (UAV) and a camera system. The camera system is developed from two action cameras, one with its infrared filter removed and replaced with blue notch filter. It is then attached to a UAV for capturing aerial images of a certain field. The images were then processed in a program written in MATLAB®. A total of 30 samples were selected in a rice field. Each sample is a 1x1-meter area. The NDVI values of the samples were first measured using Oklahoma State University (OSU) Greenseeker prototype, then the images of these samples were taken using the camera system developed. The images were then processed to get the NDVI values. Overall, the measurement of the camera system showed good consistency. The F-test conducted also implied that the system is reliable and can be used as an alternate in determining the NDVI levels in the field.**

***Index Terms*—Normalized Difference Vegetation Index (NDVI); Unmanned Aerial Vehicle (UAV); Image Processing; Remote Sensing.**

I. INTRODUCTION

One of the main problems of Philippine rice industry is low rice yield. There are factors that are needed to be considered to increase rice yield, like crop care and management. Proper management is vital to achieve successful operations in the field of agriculture. It is important to monitor water stress, biotic ecology, crop health, yield quality and, to determine the optimal amount of field inputs (chemicals like fertilizers, herbicides and pesticides) [1]. Although the country is an agricultural country, it is left behind on technologies for agriculture. Some of the techniques still used today include manual ocular inspection and observation [2]. These traditional techniques in farming management limit the comprehensive and efficient monitoring and controlling of factors that promote plant health and crop yield [3].

In the country, rice crop yield declination commonly results from known rice diseases. As an alternative to manual visual inspection studies conducted in [4-6] make use of Neural network learning algorithm for rice paddy crop health monitoring.

Other farming management techniques do not just include crop disease identification but also determination of vegetation index which is done through spectral imaging using leaf reflectance.

Leaf reflectance is one parameter associated with the health status of plants and can be used to determine the photosynthetic activity, nutrient deficiencies and stresses that the plants experience. In theory, healthy vegetation will absorb most of the visible light it encounters and reflects a large number of the near-infrared light [7]. Hence, using appropriate sensors to estimate leaf reflectance could help in precise monitoring and management of a crop field. Normalized Difference Vegetation Index (NDVI) is a technique which utilizes the near-infrared and visible bands of the electromagnetic spectrum in order to quantify the vegetation density in a specific area. [8] In a study conducted by Huang, et al [9] Formosat-2 satellite remote sensing was used to estimate the nitrogen level, leaf area index (LAI), biomass, nitrogen uptake and chlorophyll meter of three study sites with different climate conditions. This study used a number of vegetation indices, including NDVI, to estimate the said parameters. Since this study focused on satellite remote sensing, the equipment used was expensive and is not easily available to farmers. Another study which was conducted by Preeyanka Shah [10] monitored water stress of crops in crop fields using aerial-captured thermal images. The prototype used a thermal camera attached to a low-flying manned aircraft. An automated image processing of the captured images was also developed in this study. Meanwhile Berni, J., et al [11] developed a UAV helicopter platform to carry desired payload for remote sensing and vegetation monitoring operations. The sensors used multispectral and thermal cameras.

The purpose of this study is to provide a cost-efficient alternative to expensive satellite and multispectral imaging in determining the NDVI levels of the vegetation in a specific area through the use of consumer-grade equipment.

II. HARDWARE CONSTRUCTION

The chosen Unmanned Aerial Vehicle (Quadrotor type) has a maximum payload of 440 grams which is sufficient enough to carry the camera system. The camera system includes two action cameras which are responsible for taking the NIR and VIS images for NDVI processing.

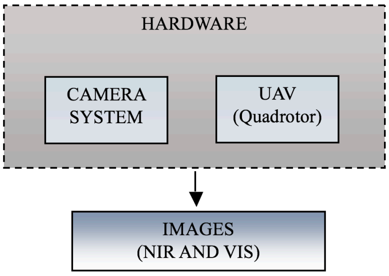


Figure 1: Hardware Block Diagram

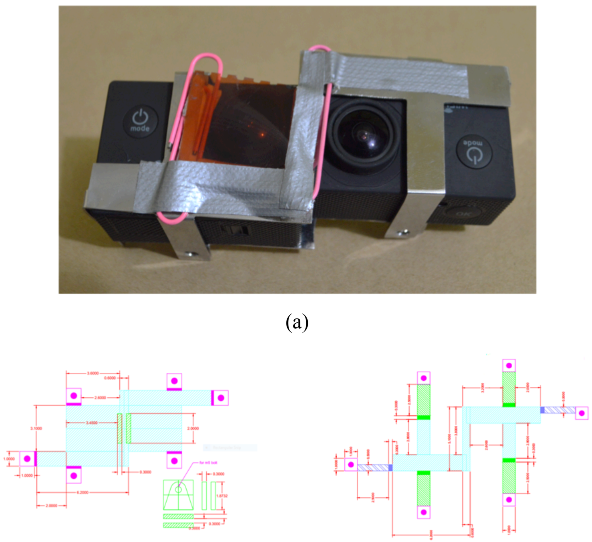
Figure 2: Cheerson CX-20

A. Unmanned Aerial Vehicle (UAV)

The UAV used is a Cheerson CX-20 as shown in Figure 2. It is a quadcopter with an estimated flight time of 15-20 minutes and a flight weight of 440 g.

B. Camera System and Case Design

The camera system uses two identical action cameras with the unit model SJ4000. One of the cameras was modified to detect infrared. The modified camera had its infrared filter removed and replaced with blue light notch filter in order to prevent the camera's CMOS sensor to perceive visible blue light frequencies. Figure 3(a) shows an image of the actual camera used. A case was designed to hold the two cameras together and its dimensions are shown in Figure 3(b) and 3(c). It is designed to position the lenses adjacent to each other in order to keep differences in the acquired images at minimal and negligible level.



(a)

(b) (c)

Figure 3: Actual image of action camera and its encapsulation

III. EXPERIMENTAL RESULTS

A program named Amihan was developed in MATLAB® to process the images acquired. Acquired images undergo five major processes as shown in Figure 4. The program has two main functions, computing for NDVI and photo stitching. The user can choose from the two functions after the startup of the program.

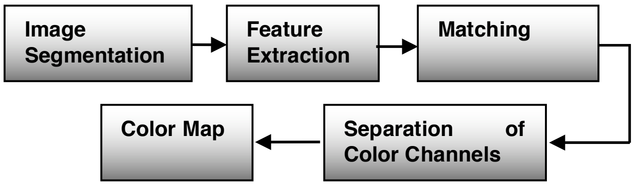


Figure 4: Software Major Sections

A. NDVI Computation

The flowchart for the computation for NDVI is shown in Figure 5.

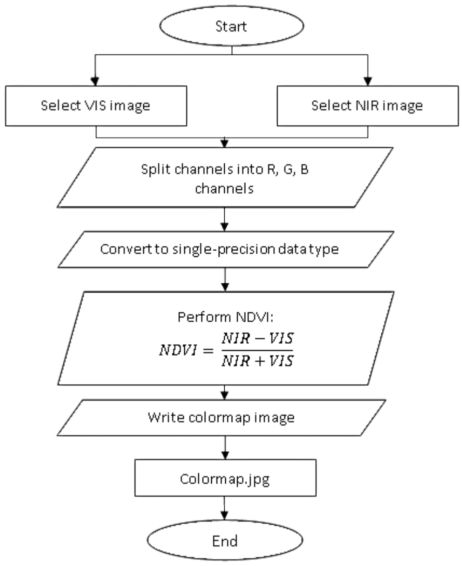


Figure 5: Flow chart for computing the NDVI

Two images acquired through the use of the camera system are selected as input for the program. One is a true color RGB image and the other one is an NRG image. Figure 6(a) and 6(b) shows an example of the input image pair.

The images then undergo image segmentation, feature extraction and channel splitting. In image segmentation, the canopy was differentiated from the soil through thresholding and masking and the resulting processed images are shown in Figure 6(c) and 6(d).

As for the feature extraction, the R, G, B values per pixel of both RGB and NGB images were extracted. The matrices of values obtained were converted to single-precision data type and then used to compute for the NDVI values of the field using the Equation (1).

$$NDVI = \frac{NIR - VIS_{Red}}{NIR + VIS_{Red}} \tag{1}$$

With the NDVI values computed, the program will write a color map image or a false color composite as a result to show the NDVI levels in the field as shown in Figure 7.

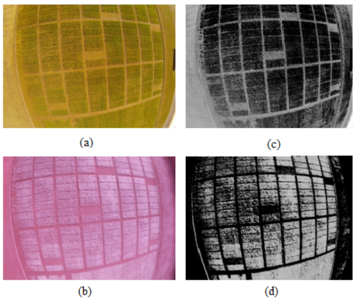


Figure 6: (a) RGB image (b) NRG image of the same field (c) Segmented RGB image (d) Segmented NRG Image

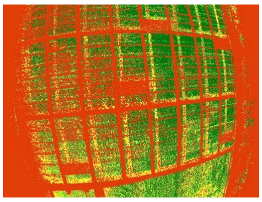


Figure 7: Color map image of the NDVI levels in the field

B. Photo stitching

The code for the photo stitching was adapted from open source library, VLFeat [12] for scale invariant feature transform (SIFT) feature extraction. The flowchart for the photo stitching is shown in Figure 8.

It starts with selecting the two or more overlapping images to be stitched. Each image selected will be converted to single-precision data type. The images will be converted to grayscale in order to get SIFT descriptors. Using the random sample consensus (RANSAC), the program will look for matches between two images by computing homography. The points with sufficient matches and homography will be stitched together and will produce an output image. If there are more than two images, this output image will undergo the same process with another image as discussed earlier until all selected images are stitched together.

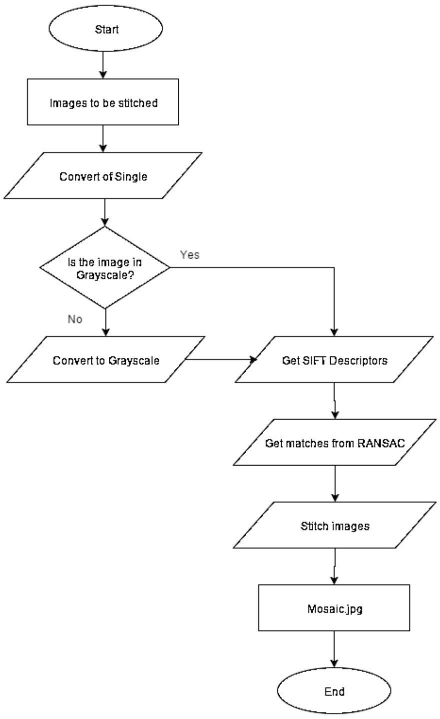


Figure 8: Flow chart for Photo Stitching

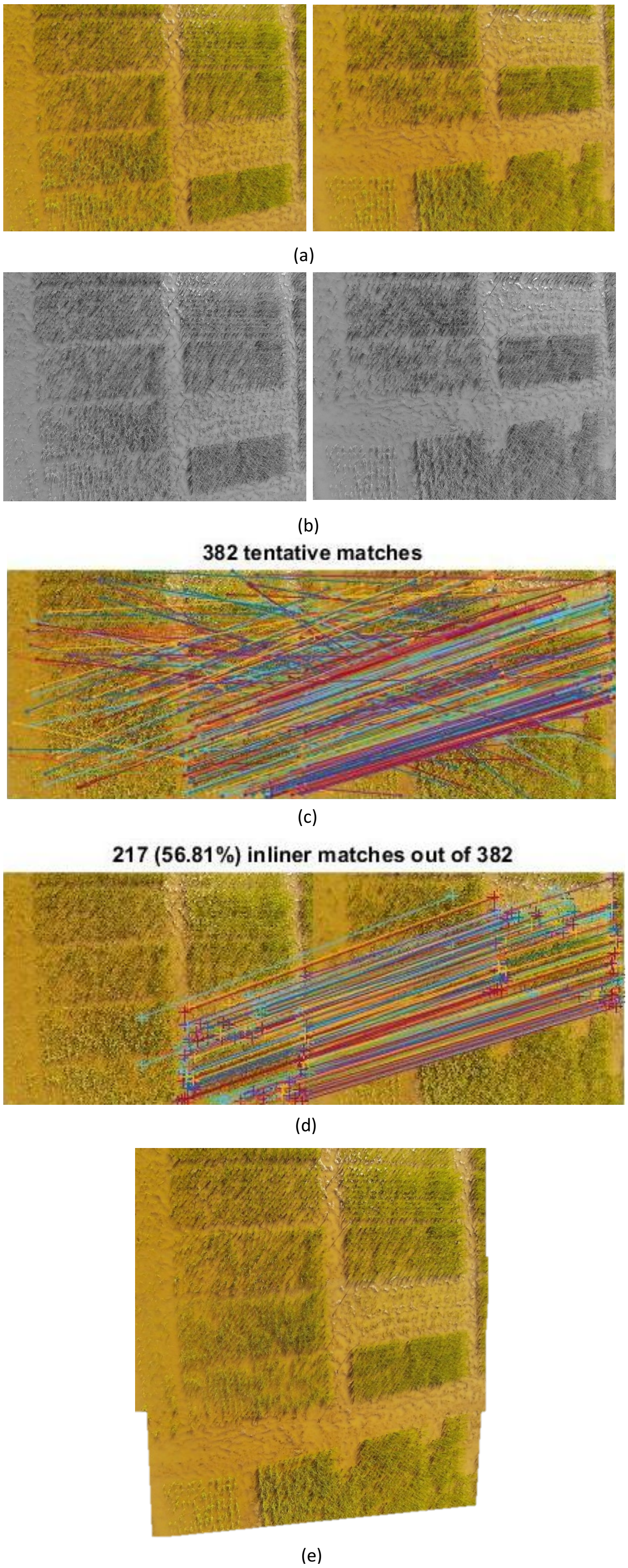


Figure 9: Photo Stitching for two images: (a) The two overlapping input images(b) Grayscale-converted images (c) Tentative matches detected between the two images (d) Matches with sufficient homography are kept while outliners are disregarded (e) Output mosaic of the two images

IV. EXPERIMENTS AND RESULTS

A. *Comparing NDVI Values Obtained Using Amihan and OSU Greenseeker Prototype*

The NDVI values measured using Amihan and OSU Greenseeker that were obtained from 30 samples are plotted as shown in Figure 10. Each sample is a 1x1-meter area in the rice field.

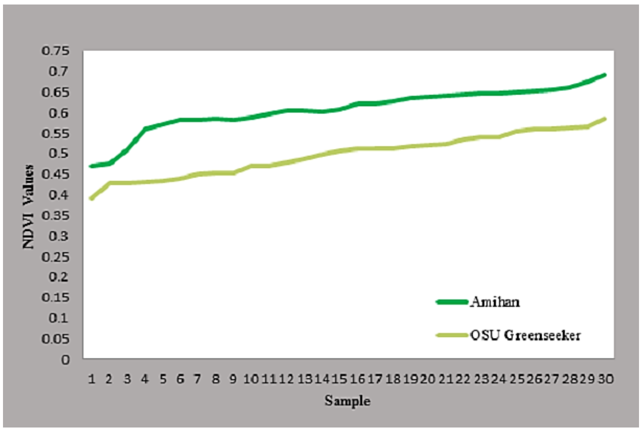


Figure 10: NDVI vs. Sample Plot of Amihan and OSU Greenseeker

In Figure 10, it can be observed that the NDVI values obtained using Amihan are higher than those obtained using the OSU Greenseeker Prototype. This could be due to the different sensing elements used in each device. However, it can also be observed that the values obtained from both devices have a similar trend to one another. In order to methodically test the equality of variances of the two sets of measured NDVI values, F-test was performed. The computed F_{stat} is 1.171744283. On the other hand, the value of F-critical from the F distribution table with a level of significance of 5% is 1.862. Since the value of F-statistical is less than the value of F-critical, the null hypothesis which states that the variances of the two data sets are equal, is accepted at 95% confidence. Having the same variances means that the value obtained using one of the devices increases or decreases in the same manner that the other does. Hence, each device can be used as an alternative to one another especially if the values are grouped accordingly into ranges wherein the difference in value does not affect much of the classification of the NDVI values.

B. *Data Consistency*

The consistency of measurement of the camera system is evaluated using five test points selected from the values using OSU Greenseeker prototype. The test points were selected using the values shown in Table 1.

Table 1
Experimental Results of OSU Greenseeker Prototype

Test Point	NDVI Value Using OSU Greenseeker
A	0.392 (minimum)
B	0.487 (mean)
C	0.440 (midway of the minimum and mean)
D	0.585 (maximum)
E	0.534 (midway of the mean and maximum)

After being determined from the data gathered, the NDVI value from each of these test points were taken 10 times each using the system developed. Then, the standard deviation for each test point was computed in order to determine the precision of measurement.

Table 2
NDVI Standard Deviation Result of the Amihan Software

Test Point	Standard Deviation
A	0.010899498
B	0.014351644
C	0.017948056
D	0.013123895
E	0.013533794

As shown in Table 2, the standard deviation from each test point is relatively small which translates to good precision. Even the highest standard deviation obtained, which is 0.017948056 has negligible effect in the classification of NDVI values.

V. CONCLUSIONS

A successful MATLAB implementation of Normalized Difference Vegetation Index determination of rice paddy crop was done in this research. Also, the modified camera system has a favorable outcome in detecting infrared region of the electromagnetic spectrum, showing good consistency and precision in five test points. The F-test conducted also implied that the system is reliable and can be used as an alternate in determining the NDVI levels in the field.

The project was successfully implemented and done; however, the proponents would like to make few recommendations for the project's future progress; use a drone with longer flight time to cover larger area, modify the device to allow the use of wireless acquisition and come up with a technique to reduce its memory consumption, and add more combinations of vegetation indices that can be analyzed by the system to achieve more accurate results.

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REFERENCES

[1] Balisacan, A. M., & Sebastian, L. S. (2006). Securing Rice, Reducing Poverty: Challenges and Policy Directions. Retrieved from http://lynchlibrary.pssc.org.ph:8081/handle/0/1062

[2] Khosla, R. (2010, August). Precision agriculture: challenges and opportunities in a flat world. In 19th World Congress of Soil Science, Soil Solutions for a Changing World, Brisbane, Australia

[3] Dobermann, A., &Cassman, K. G. (1996). Precision Nutrient Management in 20 Intensive Irrigated Rice Systems – The Need for Another Revolution On-Farm (Asia). Better Crops International, 10(2).

[4] Orillo, J.W et al (2014). Rice Plant Nitrogen Level Assessment through Image Processing using Artificial Neural Network. Retrieved from http://ieeexplore.ieee.org/

[5] Orillo, J.W et al (2014). Identification of Diseases in Rice Plant (Oryza Sativa) using Back Propagation Artificial Neural Network. Retrieved from http://ieeexplore.ieee.org/

[6] Orillo, J.W et al (2016). Rice Plant Disease Identification and Detection Technology through Classification of Microorganisms using Fuzzy Neural Network. 72:2 (2015) 1 6, www.jurnalteknologi.utm.my, eISSN 2180–3722.

[7] Holme, A.McR., Burnside, D.G. & Mitchell, A.A. (1987). The development of a system for monitoring trend in range condition in the arid shrublands of Western Australia.Australian Rangeland Journal 9:14-20.

[8] Rouse, J. W., Haas R. H., Schell J. A., &Deering D. W. (1973). Monitoring vegetation systems in the Great Plains with ERTS, Third ERTS Symposium, NASA

[9] Huang, J., Wang, H., Dai, Q., & Han, D. (n.d.). Analysis of NDVI Data for Crop Identification and Yield Estimation. Nanjing, China: State Key Lab. of Hydrol.-Water Resources & Hydraulic Eng., Hohai Univ. Retrieved from http://ieeexplore.ieee.org/

[10] Shah, P. (2014). Image Processing Aerial Thermal Images to Determine Water Stress on Crops. Retrieved from http://web.stanford.edu/class/ee368/Project_Autumn_1314/

[11] Berni, J. A., Zarco-Tejada, P. J., Suárez, L., &Fereres, E. (2009). Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. Geoscience and Remote Sensing, IEEE Transactions on, 47(3), 722-738.

[12] Vedaldi, A., and B. Fulkerson. "VLFeat: An Open and Portable Library of Computer Vision Algorithms." Retrieved from http://www.vlfeat.org/.