Image stitching for 360-degrees artificial view of chili plant using embedded system

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ABSTRACT: Chili production is vital to Malaysian economy as the national consumption has steadily increased over the years. One of the ways to increase productivity is to have an efficient pest control system. Damages on chili plants are difficult to monitor manually due to the vast number of plants per plantation. Thus, a 360-degree monitoring system with image stitching is studied in this project to augment the pest control system in chili plantation. Images were taken from an embedded camera system and the image stitching algorithm was performed on those images to obtain the overall view of the plant. This project had implemented multiple shots around the plant with a Raspberry Pi camera and evaluated the performance of image stitching using universal image quality index by using mean squared error (MSE) and structural similarity index metric (SSIM). From the experiments conducted, the most accurate results of the stitched image scored MSE = 213.34 and SSIM = 0.8 in comparison to the original image.

Keywords: *chili; precision farming; image stitching; pest control*

1. INTRODUCTION

In Malaysia, chili becomes an important crop because of the multiculturally diverse cuisine locally requires chili as the main ingredient. According to Malaysia Trade Statistics Review, Volume 1 2020, chili has the second highest import dependency ratio for crops at 78.1% [1]. Hence, various initiatives were deployed by government agencies and farmers to increase the chili production to reduce this dependency to imports.

Chili production is typically hampered by pest and diseases such as white flies, thrips, mites and aphids which caused huge losses in quality and quantity of chili production. Plant diseases are typically identified visually by workers. Considering chili plants are typically small and can span acres, this traditional method is time-consuming and tedious.

As more automated guided vehicles are employed in precision agriculture approach to dispense accurate and precise water and nutrients, there is a potential use for the camera to be deployed simultaneously to monitor the plants for potential threats.

Due to the nature of the plants, the monitoring would require a 360-degrees view to observe for any potential deformation or browning of the leaves. Therefore, the objective of this study is to attempt to stitch multiple images taken from a single camera to produce a new image representing the view of the plant with a good structural integrity to be used for further classification of the disease in pest control system.

2. METHODOLOGY

The images of the chili plant were first taken using a Raspberry Pi camera from multiple position as seen in Figure 1. Then, the images were enhanced and corrected for white-balances to compensate for variances in outdoor lighting before they were stitched using Open CV's stitching pipeline [2]. This image stitching algorithm consists of several steps such as bundle adjustment, image registration (feature detection, feature matching), image matching, color correction, surface warping, wave correction, seam finding, exposure compensation and image blending.

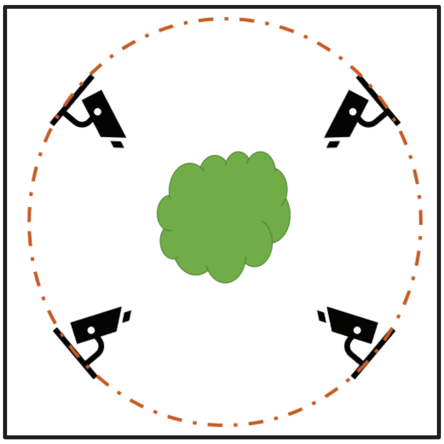

Figure 1 Single camera image capture from multiple positions.

Equation 1-4 explains the adjustment factor for the enhancement. Firstly gamma-corrected RGB value was used to calculate the sum of the pixel value ($\sum P_{c,i}(p)^{\gamma}$) of each image i, for each channel c. After that, the difference factor α is calculated between images to ensure that the overall adjustment factor is as close to 1 as possible by solving the least square function.

The gamma-uncorrected overall factor $(g_c\alpha_{c,i})^{\frac{1}{\gamma}}$ is the final adjustment factor. The α factors are depended on one "best image" which chosen by the gray world assumption [3].

$$\alpha_{c,i} = \frac{\sum_p (P_{c,i-1}(p))^\gamma}{\sum_p (P_{c,i}(p))^\gamma} c \in \{R,G,B\} (i=1,2,3,\ldots,n) \quad (1)$$

$$min_{g_c} \sum_{i=0}^{m} (g_c\alpha_{c,i} - 1)^2 c \in \{R,G,B\} \quad (2)$$

$$g_c = \frac{\sum_{i=0}^{n} \alpha_{c,i}}{\sum_{i=0}^{n} \alpha^2{}_{c,i}} c \in \{R,G,B\} (i=0,1,2,3,\ldots,n) \quad (3)$$

$$P_{c,i}(p) \leftarrow (g_c\alpha_{c,i})^{\frac{1}{\gamma}} P_{c,i}(p), \quad c \in \{R,G,B\} (i=0,1,2,3,\ldots,n) \quad (4)$$

The quality of the stitched image is computed against the original image using Mean Squared Error (MSE) and Structural Similarity Index (SSIM). The gray scale version of the images were used as presented in equation 5 and 6. If x and y are the two non-negative gray scale images, the MSE and SSIM are calculated as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} |x_i - y_i|^2 \quad (5)$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C1)(2\sigma_{xy} + C2)}{(\mu_x{}^2 + \mu_y{}^2 + C1)(\sigma_x{}^2 + \sigma_y{}^2 + C2)} \quad (6)$$

in which μ_x, μ_y represents the mean of the intensity in x and y respectively, $\sigma_x{}^2$, $\sigma_y{}^2$ represent the variances of x and y and σ_{xy} represents the covariance of x and y. C_1, C_2 are the variables that stabilize the division with the weak denominator by considering the dynamic range of the pixel-values.

3. RESULT AND DISCUSSION

The stitched images are evaluated based on mean squared error (MSE) and structural similarity index metric (SSIM). Lower MSE result and higher SSIM result is desired for the outcome. Figure 2 depicts the performance of multiple sets of stitched plants based on MSE and SSIM. MSE result for each set was a ratio of value for each set, in comparison to the highest recorded MSE, (set 3). It is evident that images in set 3 had the highest MSE at 100% (3252.03) with a very low SSIM at 18% (0.18).

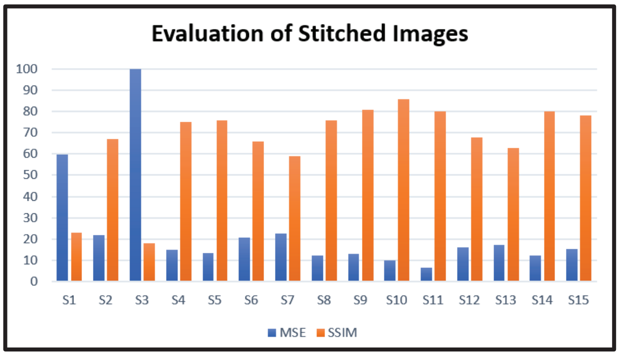

Figure 2 Graph of evaluation of stitched images

Upon inspection and can be seen in Figure 3, the leaves of the plants are actually overlapped and convoluted with the background. As the stitching pipeline relies on feature detection and matching using Speeded Up Robust Features (SURF), feature matching can be compromised and resulting in incorrect homograph.

Figure 3 Left: Original image Right: Stitched image of set 3 with convoluted background

Set 11 has the lowest MSE score at 6.56% (213.34) with SSIM=0.8 (80%). Upon inspection as can be seen in Figure 4, the images are fully focused on the plant with the leaves dominated the field of view. Hence, it can be concluded that the OpenCV stitching pipeline has the upper hand at stitching the images with the region of interest dominating the image rather than images that are highly convoluted with similar structures. This must be taken into consideration for image acquisition in the future.

Figure 4 Left: Original image Right: Stitched image of set 11 with plant's leaves dominating the field of view

4. CONCLUSION

Based on the results of the evaluation, it is necessary for the image acquisition for the purpose of monitoring the diseases on the chili plant to be conducted in close proximity to maintain the integrity of the stitched images.

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