

Design of Machine Vision System for Sugarcane Buds or Rings Detection

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Abstract—An important process in sugarcane cultivation is sugarcane preparation and planting using billets with buds and rings. Manually cutting sugarcane into billets causes low quality and productivity for cultivation. Therefore, cutting machines are needed. A proper vision system aids the cutting machine. This study was to design a machine vision program to determine good rings on sugarcane billets. The algorithm was implemented using LabVIEW NI Vision 2015 and a web camera in an enclosed box. The test was performed on sugarcane billets harvested from a farm in Buriram, Thailand. The proposed vision system can determine the sizes of sugarcane billets, colors and locations of the rings. The method for determining rings was evaluating templates using their color spectra in HSL color space. The ring was identified by matching with templates using a color matching algorithm and identified position of rings by color location algorithm. The results of real time testing showed that the machine was able to identify rings correctly at 83.33% and identify the position of rings correctly at 73.81%.

Index Terms—agricultural automation, machine vision, sugarcane cutting machine

I. INTRODUCTION

Sugarcane is the main cash crops in the northeast, the most populous area of Thailand covering 7,601.0736 km² [1]. Sugarcane propagation is performed using cut rings with root growth. The sugarcane should be cut into shorter segments called billets and they must include a ring. For planting, the rings are the most important part as mentioned above. Nowadays, the billets cutting is done by human labor, or there may be a machine to help; as a result the cutting precision is low, and the speed is low as well, partly because of labor shortage. Therefore, technology in the field of machine vision can be used to identify areas of need for the next processes for sugarcane cultivation.

There are many varieties of sugarcane. The specific characteristics of sugarcane must be used in the analysis to design a program to identify areas requiring image analysis. The physical nature of the sugarcane Ref. [2] is typically articulate with different shapes for different species and varieties, but mostly cylindrical. The arrangement of the stalk may be a straight line or a zigzag. The color will vary according to species and the

environment. Generally, there are different colors from green to purple to almost black. Different colors are caused by 2 base pigments: green from chlorophyll and red from anthocyanin. Moreover, there is also the bud, which is the most important for the cultivation of sugarcane, as a growth of the roots. The width of this region is not very consistent; the bud side is often wider than the opposite side. From the above, the most important thing to take into consideration to determine the position of ring is the color of the ring area, because it is different from other areas of the stalk, in order to be suitable for use in machine vision to identify this bud region.

At present, image processing is being used in the agricultural industry. It must take into consideration both the shape and color of the plants analyzed. The shapes such as protected area, perimeter, ferret diameter and roundness of the plant were identified by the use of color transformation from Red, Green and Blue (RGB) to Hue, Saturation and Intensity (HSI) to separate objects from the background [3]. Moreover, there is also identification of the shapes of the plant species such as apple, strawberry or potato [4]-[6]. The formatter will need to create these components, incorporating the applicable criteria that follow.

Image processing has also been used in the sugarcane industry. Sugarcane borer diseases were detected using image segmentation in a grayscale color plane to verify correspondence to the minimum average grey value, filtering and reducing noise to identify borer diseases [7]. The process used three image of the same sugarcane with intervals of 120°. The method was used to process 50 sugarcane borers images and the accuracy rate was 100%. The billet cut quality has been analyzed for use with a CAMECO harvester for autonomous sugarcane cultivation [8]. The image acquisition was a CCD camera, stereovision camera and a scanning laser rangefinder. The results of image processing to extract a part of the region are the billets, rings and buds of the sugarcane.

Before autonomous machines, sugarcane billets were justified and cut by humans. This may cause damage to the rings. This result of the inaccuracy is ring damage, harming the most important area for sugarcane growth. Therefore, the work at present is as follows. In the first section, the image acquisition equipment and methods used to acquire the image of the sugarcane are presented. Finally, program is designed for ring detection and identification of their position. The program for machine

vision uses LabVIEW National Instrument (NI Vision) 2015, which has image analysis and machine vision modules, with graphic language programming. It is easy to interface between LabVIEW and any microcontroller or Programmable Logic Controller (PLC). This makes it easy for people to use this program and to use it correctly and accurately.

II. MATERIAL

A. Image Acquisition Equipment

The images of the sugarcane billets were acquired using an enclosed box of 22 cm × 26 cm × 20 cm. Artificial light was provided by 6000K Light-Emitting Diodes (LEDs), which were equally distributed over the interior ceiling of the box. An OKER 088 web camera provided a spatial resolution of 2 Mega Pixels up to 10 Mega Pixels, and a frame rate of 30 frames per second. The camera communicated with an HP Pavilion 15-ab254sa 15.6-inch laptop via USB interface. The laptop was equipped with an Intel Core i5 Processor Laptop, 8GB RAM, 2TB HDD and an NVIDIA GeForce graphics card. The camera was facing straight downwards at a distance of 15 cm from the sugarcane billet, to get a top view of the billet as shown in Fig. 1.

B. Image Database

In this study, 42 images containing a single ring of sugarcane billet (Fig. 2) are used to illustrate and validate the proposed approach. The sugarcane was harvested in April 2018 in the region of Buriram, northeast, Thailand. The database consisted of images of various billet diameters and lengths.

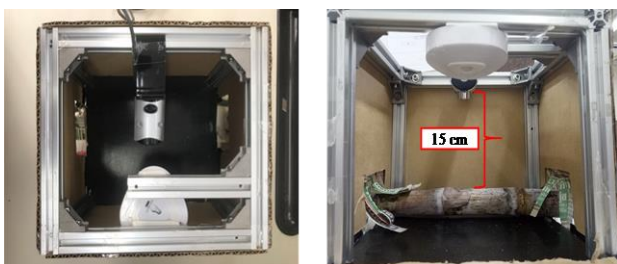


Figure 1. The image acquisition equipment from (a) top and (b) front view.



Figure 2. Sample image of sugarcane billet.

III. METHOD OF DIAMETER CHECKING AND RINGS IDENTIFICATION

A. Diameter Checking

- Color thresholding. The 32-bit RGB image (Fig. 3a) was transformed to the hue, saturation and luminance (HSL) color space [9], because a limited algorithm is sensitive to changes in the composition of the light. Part of the target was obtained by segmentation, with the threshold from the basic study being hue 3 to 127, saturation 3 to 255 and luminance 0 to 246. This is shown in Fig. 3b.
- Morphology. It has two steps. The first step was fill holds, which fills holes inside all the particles hole makes the image completely shaped up as shown in Fig. 3c. The second step was to remove small objects and eliminate excess particles from the primary particles. Primary particles were the shape of sugarcane billet as shown in Fig. 3d. Morphology includes separation or change of the shape of the particles or the object (sugarcane billet) in order to threshold the binary image. This image from segmentation, may have noise which makes the image analysis inefficient [10].
- Filter. We apply a filter to detect the edge of the billets in order to measure their diameter. The filtering process was done in two steps. The first step was to detect the edge using the Laplacian technique, a gradient filter to highlight the change in light intensity along a specific direction. This will affect the surface and edges of the image as shown in Fig. 3e. The second step was to perform convolution. Therefore, the edges are more apparent as shown in Fig. 3f.
- Clamp vertical. The vertical distance was measured from the outside to the center of the search area. The edge is found using a series of parallel vertical lines or a rake. The edges are determined based on their contrast and slope [11]. The diameter of sugarcane billets depend on the variety; here we use variety Khon Kaen 3. The relative size of the real-world image relates with the pixel size. The suitable diameter of sugarcane billets is greater than 2.5cm, with can be converted to 500 pixels as shown in Fig. 3g.

B. Color Spectral Analysis

If the color spectrum is a 1D representation of the 3D color information in an image, colors represented in the HSL model space are easy for humans to quantify. If there are n bins in the color space, the color spectrum array contains $n + 2$ elements. The last two components in the color spectrum represent black and white, respectively. Using NI Vision [9], color sensitivity can be chosen low, medium or high. Low divides the hue color space into seven sectors, giving a total of $14 + 2 = 16$ bins. Medium divides the hue color space into 14 sectors, giving a total of $28 + 2 = 30$ bins. High divides the hue

color space into 28 sectors, giving a total of $56 + 2 = 58$ bins.

In this paper, the color spectrum was created by adding many templates to analyze the spectrum of colors that stand out in any range as shown in Fig. 4.

After analyzing the spectrum of colors, the frequency spectrum was separated for dominant colors, in order to identify their positions in the spectrum. In this research, the color spectrum was analyzed using a low sensitivity setting.

From 28 templates, the frequencies of spectra were analyzed for strong colors. There were 2 groups of patterns found where the strong color was in the shade of a drab color (Fig. 5a and Fig. 6a) and dark brown (Fig. 5b and Fig. 6b). Then, both groups of patterns were used as templates for the color matching algorithm in the next process.

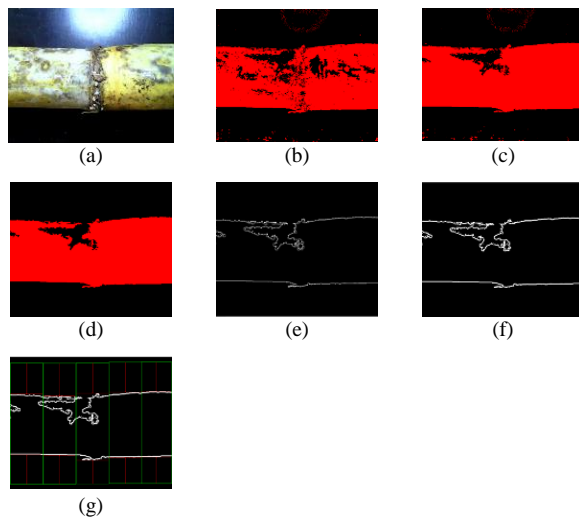


Figure 3. Sample photos of diameter checking methods: (a) image input, (b) color thresholding, (c) filling holes, (d) removing small objects, (e) Laplacian edge detection, (f) highlight detail convolution, and (g) clamp vertical rake.

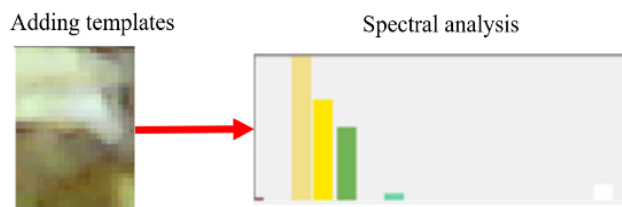


Figure 4. Diagram of color spectral analysis.

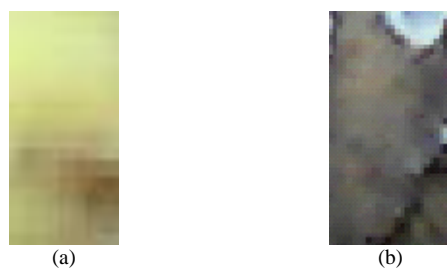


Figure 5. Sample of photo templates: a shade of a drab color (a) and dark brown color (b).

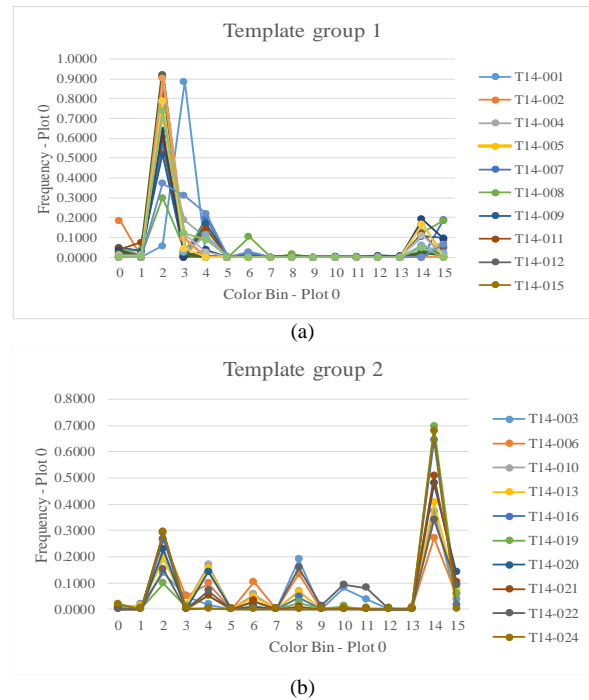


Figure 6. Two groups of the pattern of templates.

Color matching is performed in two steps [12]. In the first step, the machine vision software learns a reference color distribution by generating a color spectrum (reference color or template from spectral analysis). In the second step, the software compares color information from other images to the reference image, and returns a score as an indicator of similarity.

A match score is computed based on the similarity between these two colors spectrums using the Manhattan distance between two vectors. A fuzzy membership weighting function is applied to both the color spectrums before computing the distance between them, to compensate for some errors that may occur in the color space. The match score, ranging from 0 to 1000, defines the similarity between the color spectra. A score of zero represents no similarity between the color spectra, whereas a score of 1000 represents a perfect match.

Ring detection by color matching used 2 groups of templates for making the decision whether there were rings in the image or not. The region of interest (ROI) was assigned in the middle of the output display, which covered 720-980 pixels and 240-1010 pixels in the X-axis and Y-axis, respectively. This area was determined by the area where the sugarcane billets would be transported through the shooting frame. A ring was identified if the test image matched any template with the minimum match score of more than 800 as shown in Fig. 7.

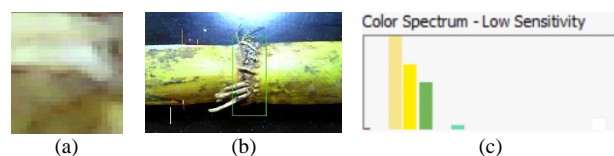


Figure 7. Color matching: (a) set the templates, (b) set region of interest (ROI) and (c) set minimum match score.

C. Color Location Method

This step is to determine the exact location of the rings on the billets suitable for integrating the proposed system with a cutting machine in future work. Color location is built upon the color matching functions to quickly locate regions with specific color information in an image.

The search step was divided into two phases. First, the software performed a coarse-to-fine search phase that identified all possible locations, even those with very low match scores. The objective of this phase is to quickly find possible locations in the image that may potentially match the template information. Instead of moving the template across the image pixel by pixel, the search process skips a few pixels between each color comparison, thus speeding up the search process. The step size indicates the number of pixels to skip. In this color matching algorithm, the amount of data used to compute the color spectrum in the image could be reduced, which speeds up the search process. The initial search phase generates a list of possible match locations in the image. In the second step, a more precise location could be found using a hill-climbing algorithm.

The color location method (Fig. 8) is similar to color matching, therefore there are 3 main steps. First, create the templates for image referencing. Second, setup the match score and the number of matches. In this step, the number of matches is set to at least 10 and the minimum match score of more than 880; the search strategy is conservative and the color sensitivity uses a medium level as shown in Fig. 8. Finally, it is calculated using a matching algorithm and the result is the position of the rings.

IV. RESULTS

The program and equipment were setup in a lab scale experiment. Images were taken from a laptop connected with the camera installed in an enclosed box. Images were taken while sugarcane billets with 42 rings manually transported past the camera shooting area as shown in Fig. 9a. All of the sugarcane billets were previously proven that they qualified for cultivation use.

The proposed vision application was run with real time capability. There were three tests performed in order to identify rings on a sugarcane billet that is suitable for cultivation. The tests included checking sugarcane diameter, matching its color with the templates, and identifying the position of the rings. Once a quality sugarcane billet with a ring moved into the frame, the green light appeared (Fig. 9b). The test results are shown in Table I.

A. Result of Diameter Checking

The diameter obtained from the clamp vertical rake has the result in pixels. A suitable diameter for a Khon Kaen 3 sugarcane billet for cultivation is larger than 2.5 cm or more than 500 pixels in the machine vision system. The system performed 90.48% correct.

B. Result of Rings Detection

For the color matching algorithm, there are true or false results. If an image has a minimum match score of more than 800, the decision will be a true. Otherwise, it is false. The rings detection had a result of 83.33%.

C. Result of Rings Location

The color location algorithm has two steps. First, there is similar color matching, which checks for a match between image templates and images input. Second, an algorithm gives the position as a pixel when identified rings are observed. The position of the pixel has benefits for determining the position for billet cutting in the real world. Based on the algorithm used in the rings location method with matching color at least 880 and 3 matches, 31 of 42 rings (73.81% of the rings) were found.

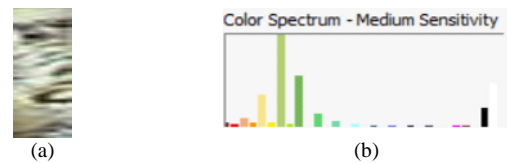


Figure 8. Color location: (a) set the templates and (b) set values.

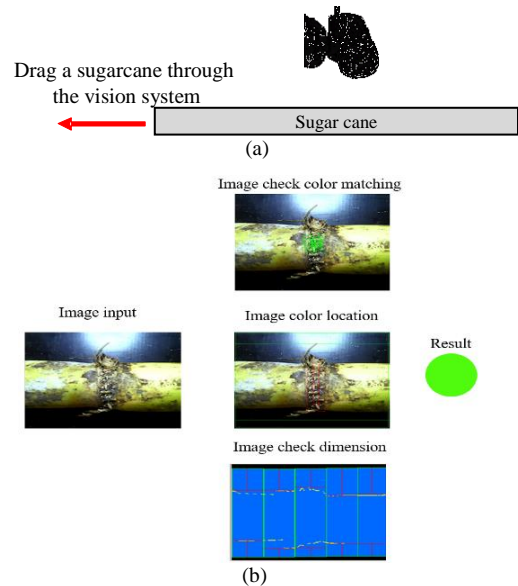


Figure 9. Set up of experiment: (a) the billet moving through the vision system and (b) display of the program.

TABLE I. THE RESULT OF ALL LABORATORY TESTING

	Result of Testing 42 sample images		
	Diameter checking	Rings detection	Ring location
The quantity of images detected (images)	38	35	31
The percentage of image detection (%)	90.48	83.33	73.81

V. DISCUSSION

A vision system for machines is designed to find rings in sugarcane billets of Khon Kaen 3 variety which have different sizes and physical characteristics. The colors of rings are in two main groups, according to a spectrum of

colors. In addition, divided some billets have soil attached to the stalk. All of the above make automated detection of rings challenging.

The diameter checking of billets in the program has been used and the process is effective. We have used the average value of thresholding in HSL color space for sugarcane stalk segmentation. This color location may be useful for application to calculate the precise position when cutting sugarcane billets.

The color matching algorithm indicates there may be a group of templates apart from the two groups in this study. This may be the reason for the inspection of rings not being fully effective. Ring location requires color matching first, then location of the position. In this study, we used medium color sensitivity in collaboration with color matching to achieve proper precision.

This paper presents an algorithm for vision system using only one camera. The percentage detection was from 73-90%, which is not considerably different from using many cameras [8] or capturing the objects from various views [7]. Certainly applying a more complex system including a variety of equipment could result in more accuracy. However, developing a simple and low-cost system, which is competitive with the use of multiple devices, is necessary.

VI. CONCLUSION

The results show that machine vision can be used to detect rings of sugarcane billets, as part of the development of a fully autonomous billet cutting machine. The vision software, with its diameter checking, color matching and color location, showed acceptable results with the Khon Kaen 3 variety of sugarcanes.

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