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Identification of Sugarcane Nodes Using Image Processing and Machine Vision Technology

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Abstract: An algorithm was designed for mechanizing sugarcane planting by machine vision system and image processing method. This algorithm uses convolution, threshold and look-up table operations for identification of sugarcane nods and sends the cut-point position of two consecutive nodes to microcontroller. The recognition algorithm which was used with right sobel matrix has 2.08±0.30% error. The right sobel matrix was assigned as the best mask matrix with the variance and standard deviation of 8.82 and 2.97, respectively. The precision of nods identification in sugarcane stalk by mentioned algorithm was estimated to be 97.92±0.3%. The test of this image processing method showed that the total running time of one image processing was less than 0.500 sec.

Key words: Convolution, image processing, machine vision, mask matrix, sugarcane node, threshold

INTRODUCTION

Sugarcane (*Saccharum* sp.) is a clonally propagated grass of the Gramineae family characterized by a high degree of polyploidy and is a crop of major importance providing about 65% of the world sugar. Reproductive tissue is harvested as the economic product in nearly all field crops but this is not the case in sugarcane. In sugarcane, the stalks are the harvested tissue and stalk size has a major influence on yield. There has been virtually some research reported on the variation in size of individual stalk internodes with position on the stalk and with crop growth (Zambrano *et al*., 2003; Sinclair *et al*., 2005).

Sugarcane planting with traditional methods is costly, time-consuming and necessary compression of buds in the field is not achieved easily because of stalk planting in sugarcane. In tradition planting method, great human force and high volume of sugarcane stalk in hectare is required. To solve this problem and mechanizing of sugarcane planting, we suggest the application of machine vision system and image processing methods to identify nodes from sugarcane and to plant it as a seed by planting machines. Many studies have been done in image processing method for contaminant removal from wool (Zhang *et al*., 2005), discrimination of hard-to-pop popcorn kernels (Yang *et al*., 2005), measurement of hot formed parts (Dworkin and Nye, 2006), weed control system for tomatoes (Lee *et al*., 1999), lentils grading (Shahin and Symons, 2001) and sorting of apple (Shahin *et al*., 2002). Edge detection is an essential technique in many image processing applications such as object recognition and motion analysis. From the view of accuracy, this technique can be classified into pixel-level and subpixel-level edge detection. Early edge detection method employed local operators to locate edge with approximately computing the first derivative or second derivative of the image gray level step in the spatial domain, Prewitt, Sobel, Marr-Hildreth and Canny operator are examples of pixel-level edge detection methods. Short running time is the advantage of pixel-level edge detection method (Dong *et al*., 2006).

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This research was done to design and evaluate an identifying algorithm for sugarcane nodes by using image processing and machine vision system. In order to design an image processing system one should select a reasonable algorithm in first and then apply the required hardware.

MATERIALS AND METHODS

For capturing image from sugarcane stalks during time intervals in proportion to carrier belt speed, a CCD camera (CCD-TVR128E, Sony, Japan) was used. These images were digitized through the use of image card and stored as a two-dimensional array. Each value in the array had an integer representing the light intensity of the corresponding pixel (picture element). Monochrome images are stored as eight-bit integer values in each array position while color images were typically stored using 24 bits per pixel, with eight bits representing the intensity of each of red, green and blue light components (Khalili, 2000; Dworkin and Nye, 2006). A typical digital imaging system is shown in Fig. 1. The processing power of computer used in this research was 2/4 GHz. The related Digital data were processed by using algorithm and the location of nodes was recognized. The algorithm used in this study for identification of nodes was shown in Fig. 2. This study was conducted in triplicate in the Center of Science and Research of the University of Islamic Azad University of Tehran during 2006-2007.

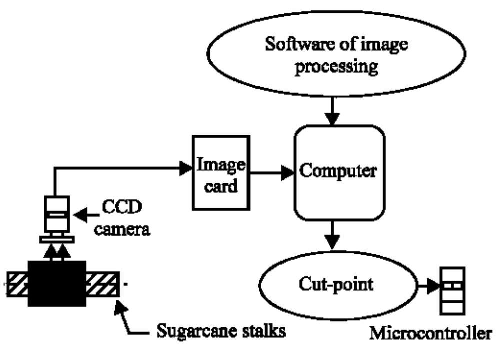

Fig. 1: Schematic representation of image processing system

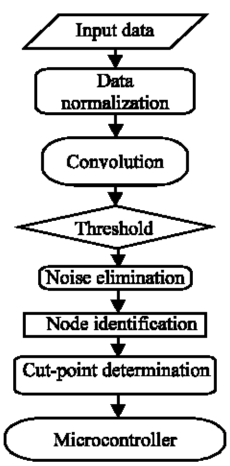

Fig. 2: Identification algorithm for sugarcane nodes

RESULTS AND DISCUSSION

Normalization and Convolution of Image Pixel Values

Each color in RGB system had maximum light intensity of 0-225 for 8 bit which was obtained using Eq. 1 of RGB amounts for every pixel (Eslami and Nazemi, 1998).

$$P(X,Y) = B\times 2^{16} + G\times 2^{8} + R \tag{1}$$

In fist stage, the resulted data form Eq. 1 was normalized to increase calculation rate according to Eq. 2 (Nakajima *et al*., 2003).

$$NVP = \frac{R+B+G}{3} \tag{2}$$

Normalized values of pixel (NVP) were about 0-225 which could be included in a byte (8 bit). Normalization had no adverse effect on the identification of sugarcane nods (Fig. 3a). In second stage, convolution operation was used for identification of sharp edges. This operation combined the amount of pixels in order to obtain desirable results (Eslami and Nazemi, 1998; Kurita *et al*., 1998; Riesenhuber and Poggio, 1999). Convolution operation was done using the Eq. 3.

$$C(X,Y) = \frac{\sum_{i=1}^{M}\sum_{j=1} P_{i,j}(X,Y)\times M_{i,j}(X,Y)}{\sum_{i=1}^{m}\sum_{j=1}^{n} M_{i,j}(X,Y)} \tag{3}$$

where, C(X, Y) is pixel value after convolution, P(X, Y) is original pixel value and M(X, Y) is convolution mask matrix. Different characteristics of images can be obtained with changing of M(X, Y) matrix. The convolution image was shown in Fig. 3b.

Eliminating Noise from Original Image Pixels

Threshold function was used for eliminating noise and reveal node according to Eq. 4, which was done as look-up table operations on the image pixels (Eslami and Nazemi, 1998).

$$TF(X,Y) = \begin{cases} 0 & C(X,Y)\langle K \\ 225 & C(X,Y) \geq K \end{cases} \tag{4}$$

In which TF(X, Y) is threshold function and k = 60 that was obtained by error and trail. Therefore, image pixels values were changed to 0 (for background) and 225 (for nodes) and low light intensity pixels were eliminated. The threshold image of sugarcane stalk was shown in Fig. 3c. Resulted images were changed to negative mode in order to further elimination of probable noises using LUT function (5) (Eslami and Nazemi, 1998; Khalili, 2000).

$$NF(x,Y) = 225 - TF(X,Y) \tag{5}$$

where, NF (X ,Y) is negative function. In this case, image pixels values were changed to 0 (for nodes) and 225 (for background). The negative image of sugarcane stalk was shown in Fig. 3d.

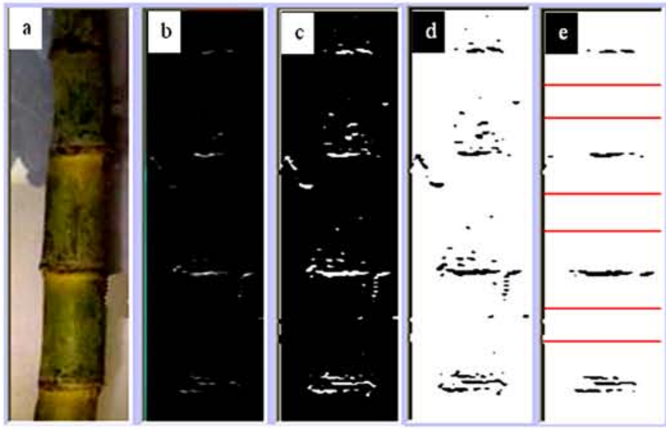

Fig. 3: (a) Primary image, (b) image after convolution operation, (c) image after using threshold function and (d) negative image and (e) location of cutting points

Algorithm for Node Identification

Node identification algorithm firstly evaluates row by row image pixels from left corner. With progress of this stage, the number of pixels which have zero amounts in a row were calculated and divided by total pixels in a row. If the resulted value was grater than 0.154, it could be considered as node (Fig. 3d). Therefore, algorithm identified the nodes by using the following comment:

If NNP (number of node pixels)/NTP (number of total pixels)> 0.154 then
Node = true
Else
Node = False

In the next stage, identification of cut-points in sugarcane stalk occurred by algorithm using the Eq. 6, 7 and 8.

$$TS = \frac{H(i+1) - H(i)}{3} \tag{6}$$

$$FP = H(i) + TS \tag{7}$$

$$SP = FP + TS \tag{8}$$

where, TS is one third of distance between two consecutive nodes, H(i) is the location of node = i, H(i+1) is the location of node = i+1, FP is location of the first cut-point, SP is location of second cut-point. In Fig. 3e, the location of nodes, background and cut-point were displayed by dark, white and red colors, respectively. As shown in Fig. 4, a graphical user interface (GUI) was designed for mentioned algorithm by visual basic programming (visual basic No. 6.0).

As it was shown in the left side of Fig. 4, the sent image from camera will be shown real-time. With setting the time interval between two images or processing speed using the scrollbar and pushing start button, images will send out to above section in the right side and image processing stages will occur. Finally cut-point locations between two consecutive nodes will be sent to micro-controller. Designed GUI had two manual processing and automatic processing units. In manual processing unit,

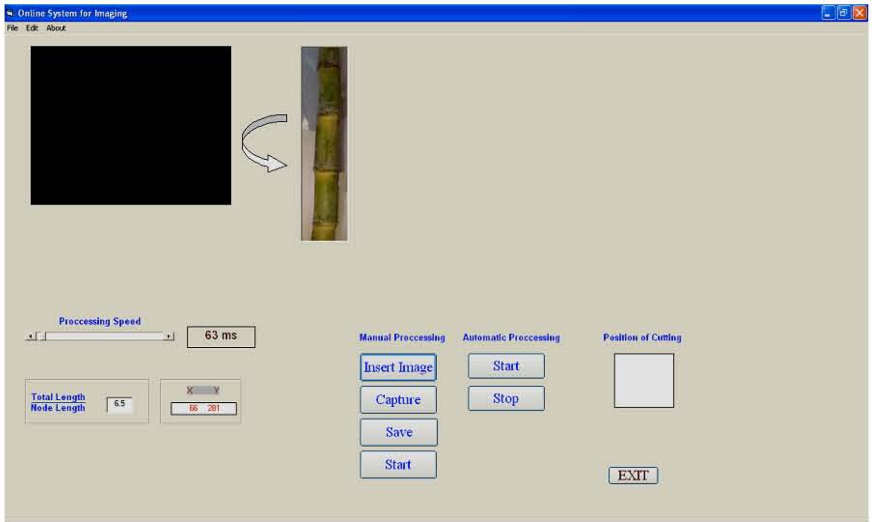

Fig. 4: Graphical User Interface (GUI) for identification of sugarcane node

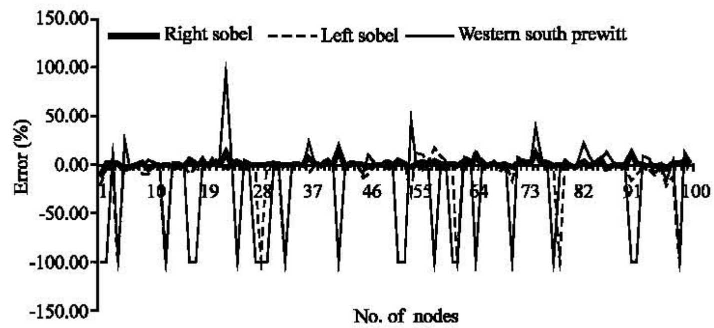

Fig. 5: Error percentage of right sobel mask matrix with others

desirable image is selected by pushing Insert image button and will be processed when start button pushed. In this way, location of cut-points will be appeared in the position of cutting. In automatic processing, at first, processing speed should be set by scrollbar and then start button in right side should be pushed. In the both units, the pixels proportion of nodes could be changeable.

Appropriate Mask Matrix for Convolution Operation

Standard matrixes were used for selecting suitable matrix mask on 100 sugarcane node samples in 39 images and right sobel, left sobel, east perwitt, west perwitt and western south perwitt were evaluated. Only the right sobel could be able to identify the node locations in dark stalks and low resolution pictures. SPSS statistical analysis showed that the average and standard errors were 2.08 and 0.30%, respectively (Table 1). Error percentage of right sobel was compared with other mask matrixes in Fig. 5 and 6. The X axel with zero error percentage indicates the real location of nodes in sugarcane stalks. It is clear that the error percentage of right sobel mask matrix is the lowest.

The right sobel matrix was assigned as the best mask matrix with the variance and standard deviation of 8.82 and 2.97, respectively. In addition to identifying all of sugarcane nodes by using the suggested algorithm, only 97.92±0.3% of the real locations of nodes was determined. This was due to

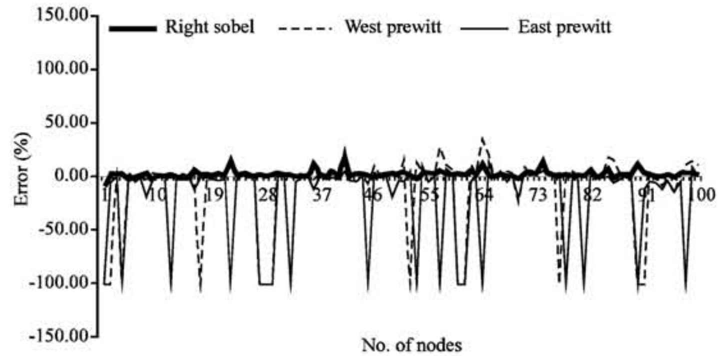

Fig. 6: Error percentage of right sobel mask matrix with others

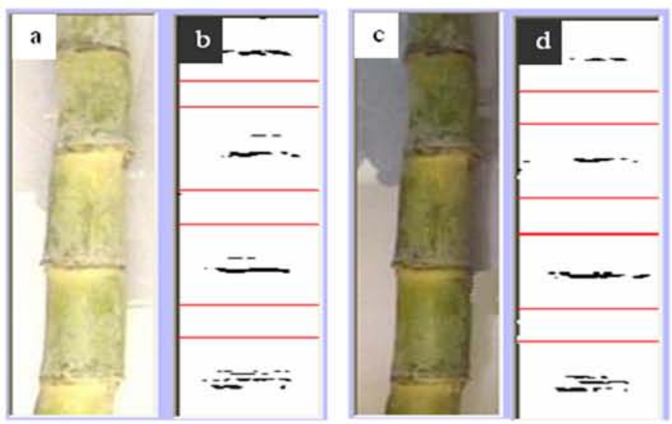

Fig. 7: (a-b) Before and after processing image of sugarcane stalk with high light intensity, (c-d) Low light intensity

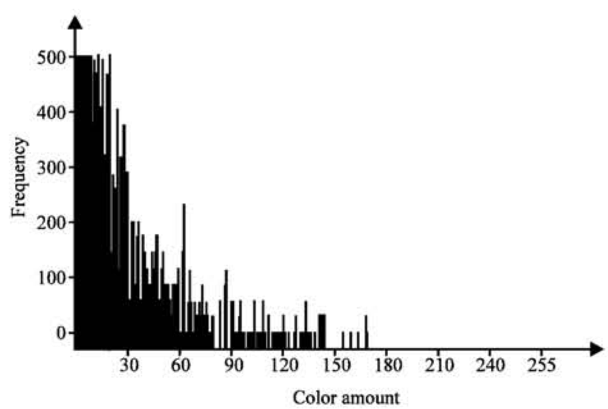

Fig. 8: Histogram of image data after convolution

Table 1: Statistical analysis of percent error of node location by standard masks

Statistics	Right sobel	Left sobel	Western south perwitt	West perwitt	East perwitt
Average error (%)	2.08	11.90	27.94	17.63	21.31
Number of nodes	100.00	100.00	100.00	100.00	100.00
Maximum error (%)	15.00	100.00	100.00	100.00	100.00
Error limit (%)	15.00	100.00	100.00	100.00	100.00
Variance	8.82	619.50	1696.72	1016.24	1388.83
Standard deviation	2.97	24.89	41.19	32.62	37.27
Standard error (%)	0.30	2.49	4.12	3.26	3.73

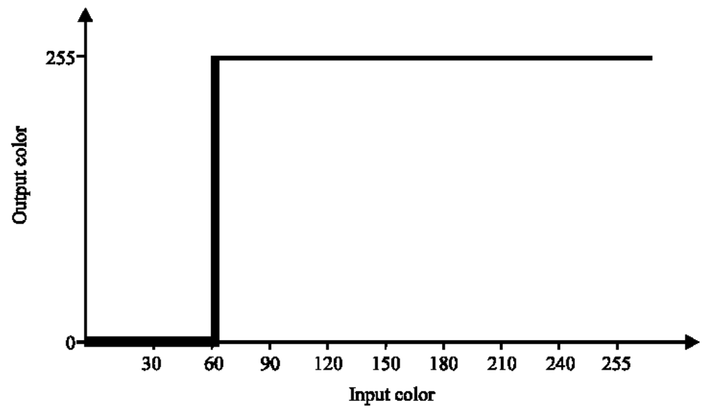

Fig. 9: Image data after threshold operation

irregular geometrical shape of nodes. Results showed that light intensity had not significant effect on the identification of node location in this method (Fig. 7). As the histogram (Fig. 8) indicates, the variation of image data with values less than 60 is very high and this noise can be eliminated. Therefore, by using threshold operations (Fig. 9) the value of pixels are change to 0 and 225.

CONCLUSION

In present study, a method was introduced for identification of node location on the sugarcane stalk. This approach consists of six steps of capturing, digitizing, normalization, convolution, threshold and negative operation. All of sugarcane nodes were identified using the suggested algorithm. The advantage of this image processing system was high processing speed with a run time less than 0.500 sec and high precision with a relative error of measurement no more than 2.08±0.30%. These results are in agreement with that of obtained by Dong *et al*. (2006). Right sobel edge correction mask matrix had minimum variance and standard deviation in comparison with other masks; therefore, it was selected as the best mask for identification of sugarcane nodes. The proportion of node pixels to total pixels in a row depend on factors such as image wide, camera height from sugarcane stalks and camera magnification. When camera height was 1 m, the number of pixels in row was 70 pixels and camera magnification was selected in minimum amount, the proportion of node pixels to total pixels was obtained as 0.154.

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