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DETECTION OF HARVESTED BEANS FROM A CLUSTER SAMPLE

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Abstract

Detection of individual objects from an image of the cluster sample of harvested beans is one of the challenges for automatic systems. Existing work uses the watershed algorithm to separate objects in contact. However, due to variation in the physical properties of the harvested beans, the watershed algorithm performs inefficiently. In this paper, we propose a novel method to separate objects using their V-notch topology feature. The experiments conducted on harvested black-eyed peas, soybeans, and kidney beans with different sample weights show that the proposed method performs better than the watershed algorithm. The average accuracy of detecting whole objects from sample images is almost 94% for black-eyed peas, 97% for soybeans, and 95% for kidney beans when processed with the proposed method, and that is approximately 55% for black-eyed peas, 65% for soybeans, and 35% for kidney beans when processed with the watershed algorithm.

1. Introduction

Beans are one of the essential elements in the daily food of humans and animals. Nutritional values of beans supplement for good health [1]. Over the

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period, the beans market rose at a quick pace. The health consciousness among people ascribes a rapid expansion of the beans market [2]. Evaluating the physical properties of beans is important before consuming them in food products. For this purpose, automatic systems need to detect individual objects from a sample of beans [3]. Placing sample objects in a cluster form effectively utilizes the imaging window and saves time. However, in the cluster form, the neighbouring objects contact each other. An image processing technique separates objects in contact. Broadly, the literature suggests different methods for detecting objects from the cluster samples of grains, beans, fruits etc. [4] proposed an active contour method for segmenting the rice kernels in contact. In this method, an inverse gradient vector generates the centre of a field for each kernel and takes the centre reference to initiate contours. A completed contour separates contacting kernels. The method suggested in [5] separates contacting grains using an ellipse-fitting method. This approach applies the least square method for fitting an ellipse to the edges between contacting grains and performs morphological operations to separate grains. [6] proposed a method for detecting soybeans from a cluster sample. This method implements the morphological operations to separate contacting objects. [7] modified the watershed algorithm to incorporate the extended maxima transform for separating objects in contact. Authors report an improvement in the object separation process as the modified watershed algorithm avoids over-segmentation. [8] suggested an image processing scheme based on image compression, mean shift filtering, colour convolution, and Gaussian filtering to detect kernels on maize ear with better accuracy.

However, the methods suggested in the literature utilize the threshold values or morphological operations like opening-closing or gradients computed on pixel intensities. The sensitivity to local minima and noise degrades the performance of these methods. Therefore, to address the limitations of the existing methods, we propose a method that utilizes the V-notch topology features of the contacting objects. We observed that our method minimizes loss of object information while separating objects.

2. Materials and Methods

A. Sample. This study considers black-eyed peas, soybeans, and kidney beans for experiments. We randomly collected one test sample of harvested beans for each of these types. The collected test sample contains normal beans and the anomalies like organic, inorganic foreign matters, discoloured/ damaged beans, insect-infected beans, immature beans, shrivelled beans, split/ broken/ cracked beans. The weight of each test sample is 100 grams. For experiment, we divided every 100 grams into 10, 20, 30 and 40 grams.

B. Image Acquisition. Figure 1 shows the image acquisition setup implemented to capture images of the collected samples of weights 10, 20, 30 and 40 grams. It consists of an HP Scanjet g4050 scanner embedded with the charge-coupled device sensor to help in acquiring better quality images. Plain white paper background and backlight arrangement enhance the contrast level between sample beans and the background, which is helpful to detect objects from the captured images. This setup produces 2-Dimensional colour images of the size 3500×3500 pixels scanned at the resolution of 600 pixels/ inch. We place sample objects on the imaging platform in random but non-overlapping positions. Neighbouring sample objects contact each other.

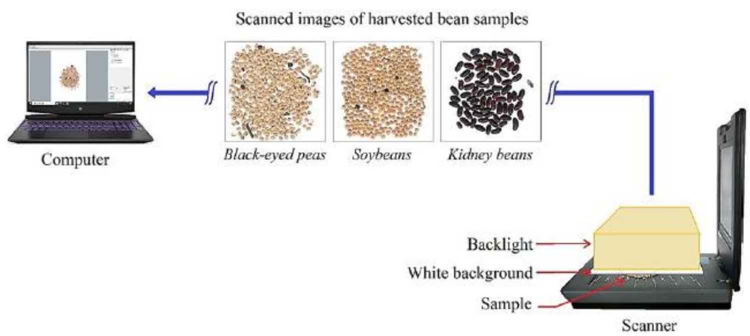

Figure 1. Setup for image acquisition.

3. Proposed Method for Object Detection

Detection of individual objects from an image is a major concerns. For an automated system, detection of individual objects is possible only if the contacting objects in a sample image appear separated. For this purpose, the proposed scheme converts the sample image into a binary image and processes it to extract topology features for each pair of contacting objects.

A. Image Binarization and Noise Removal. Image binarization segments a sample image into objects and the background using the global thresholding technique [9]. Pixel intensities of the white background are considered the global thresholds. Then, a sliding window [10] of size 10×10 moves through every pixel of the binary image to capture dust particles and flip their pixel intensities to the pixel intensity of the background.

B. Separation of Contacting Objects. Figure 2 shows the topology of two contacting black-eyed peas with their contact confined by the end pixels (refer to P and Q). We observed the same with soybeans and kidney beans. Similarity in pixel intensities of contacting objects makes finding the actual contact difficult. For alternate solution, we reconstruct a contact by processing the binary image obtained after noise removal.

For reconstructing a contact, we identify pixels P and Q based on the topology of contacting objects. As shown in Figure 2, the boundaries of contacting objects create two V-notches oriented in the opposite directions. Pixels P and Q lie at the corners of these V-notches. After validating a pair P and Q, a linear staircase path reconstructs the contact.

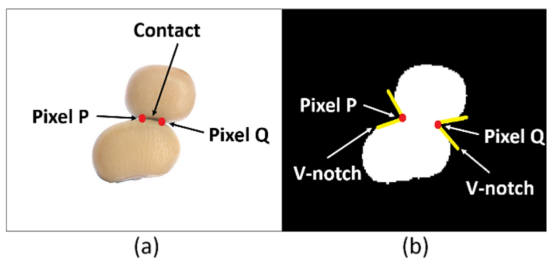

Figure 2. Black-eyed peas with the (a) contact and end pixels and (b) V-notches.

(1) Finding a V-notch and its corner pixel. We utilize the pattern matching window technique [11] for finding V-notches and their corner pixels. Figure 3 shows the pattern matching windows $M_0, M_1, M_2, M_3, M_4, M_5, M_6, M_7$ we designed for detecting V-notches and the eight categories $S_0, S_1, S_2, S_3, S_4, S_5, S_6, S_7$. Each pattern matching window M_k, for $0 \le k \le 7$ moves through every pixel of the sample image. If its green-colored pixel form matches a form in the sample image, the matched pixel form is considered a V-notch. It categorizes the detected V-notch by checking conditions mentioned in Table 1. '0' of the detected V-notch, corresponding to '0' of the green-colored pattern, is the corner pixel. It stores all identified corner pixels of category S_k in a binary image $BS_k (0 \leq k \leq 7)$ at their original location. BS_k has dimensions of S_k.

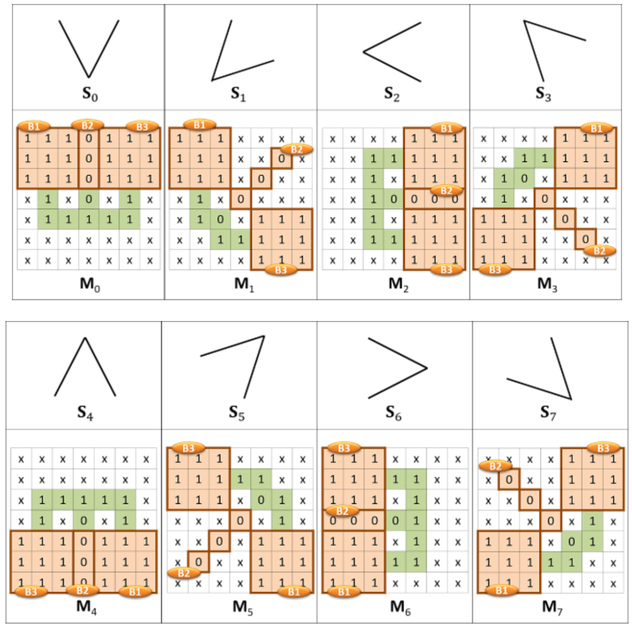

Figure 3. V-notches along with the patterns.

Tebla 1. Categorization of a V-notch.

for a pattern matching window M_k

if $(B_2 > 0)$ and $[(B_1 > 2)$ OR $(B_3 > 2)]$ and $(| B_3 - B_1 | \leq 2)$ then

category of the detected V-notch is S_k;

elseif $(B_2 > 0)$ and $[(B_1 > 2)$ OR $(B_3 > 2)]$ and $(| B_3 - B_1 | \leq 2)$ then

if $(B_1 < B_3)$ then category of the detected V-notch is $S_{(k-1 \bmod e)}$

if $(B_1 > B_3)$ then category of thedetected V-notch is $S_{(k+1 \bmod e)}$

else neglect the detected V-notch. It is not created by the touching objects:

(2) Validating *P* and *Q*, and Reconstruction of a contact. *P* and *Q* at the shortest distance only constitute a valid pair. For this purpose, the proposed algorithm visits each corner pixel stored in BS_k, for $0 \leq k \leq 7$. It considers the visited corner pixel as P and searches its Q in the images $BS_{(k+3, \bmod 8)}$, $BS_{(k+4, \bmod 8)}$, $BS_{(k+5, \bmod 8)}$ for $0 \leq k \leq 7$. For reconstructing a linear staircase path, the proposed method refers to column and row-wise distances between P and Q.

4. Results and Discussion

We compared the performance of watershed algorithm and the proposed method. Table 2 refers to accuracies in object detection. For illustration, Figure 4 shows the images of black-eyed peas processed for 20-gram sample.

Table 2. Accuracies of Watershed Algo. and the proposed method.

Type of beans	Sample weight (in grams)	Real count of objects	Object separation through Watershed algorithm		Object separation through the proposed method	
			Count of objects	Accuracy (in %)	Count of objects	Accuracy (in %)
Black-eyed peas	10	88	47	53.41	86	97.73
	20	172	86	50.00	160	93.02
	30	255	145	56.86	236	92.55
	40	344	201	58.43	325	94.48
Average =			-	54.68	-	94.44
Soybeans	10	92	60	65.22	88	95.65
	20	187	129	68.98	181	96.79
	30	275	173	62.91	263	95.64
	40	366	236	64.48	360	98.36
Average =			-	65.40	-	96.61
Kidney	10	20	7	35.00	19	95.00

beans	20	38	11	28.95	36	94.74
	30	58	21	36.21	55	94.83
	40	79	30	37.97	75	94.94
Average =			-	34.53	-	94.88

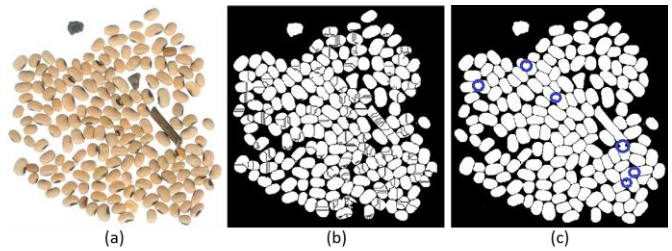

Figure 4. Black-eyed peas after (a) scanning, application of (b) watershed and (c) the proposed algorithms (blue circle indicates contact not separated).

5. Conclusion

Our comparative study shows that the proposed method performs better than the watershed algorithm. The proposed object separation method utilizes the V-notch topology feature of the contacting objects to overcome the drawbacks of the watershed algorithm. The proposed method avoids splitting objects of the sample images into parts. Higher accuracy of the object separation method minimizes the loss of object information. Also, there is no significant effect of the change in sample weight object separation.

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