



Journal of
**Software
Engineering**

ISSN 1819-4311



Academic
Journals Inc.

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A Study on Recognition Method of Fruits Based on Machine Vision

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ABSTRACT

An apple recognition method with (R-G) color difference was presented. The improved OTSU algorithm segmented image to increase the operation speed. Through mathematical morphology processing and region filling, repairing and marking, the centroid of connected region was calculated. The experimental results show that under the influence of different light and background, apples that are not shaded seriously can be better identified. The total recognition rate reaches 86%. The color difference information, the improved OTSU algorithm and centroid acquisition provides a visual basis for realizing accurate identification and positioning of fruit and vegetable robot.

Key words: Apple detection, machine vision, recognition method, feature extraction

INTRODUCTION

Under natural conditions, it was the foundation and key technology of fruit and vegetable robot vision system to realize accurate recognition and position of fruit (Hannan *et al.*, 2007; Si *et al.*, 2009). At present, researchers in the field of machine vision had put forward some fruit recognition methods in natural environment (Nalpantidis and Gasteratos, 2010; Arivazhagan *et al.*, 2010). However, the fruit images collected in natural light had the complex background: Fruits were affected by the illumination as well as fruit appearances had various changes due to fruit shelter, so the fruit recognition was affected greatly (Feng *et al.*, 2013; Vera-Rodriguez *et al.*, 2012; Xiong *et al.*, 2013). Based on previous study results, apple recognition process was treated as an example in the natural environment, OTSU algorithm was improved using color difference image to mark the area and calculate the centroid of connected region and finally the fruit was located.

MATERIALS AND METHODS

Image filtering: The median filter was a nonlinear method in restraining noise. The given N figures were ordered according to value. When N was odd, the numerical value in the middle position was called median value of N figures; when N was even, the mean of two numerical values that were located in the middle position was called median value (Bulanon *et al.*, 2008), which was denoted as $\text{med}(a_1, a_2, \dots, a_n)$.

A color image could be represented as:

$$V_i = (R_i, G_i, B_i) \quad (i = 1, 2, 3, \dots, N) \quad (1)$$

There were a set of K vector in the given window, namely:

$$W = \{W_i\} (i = 1, 2, 3, \dots, K) \quad (2)$$

According to the median filter definition, the algorithm steps were as follows:

- First to calculate of distance S_i between window vectors was as follows:

$$S_i = \sum_{j=1}^K |W_j - W_i| \quad i=1, 2, 3, \dots, N \quad (3)$$

- To choose minimum S_{\min} from S_i
- Vector corresponding to S_{\min} was output median vector

Figure 1 was before and after median filtering images; obviously, in the filtered image the color was more even, the noise was restrained effectively and kept the edge features of fruit, thereby favoring the apple segmentation in the next step.

Image segmentation

Color parameters: Currently, segmentation color features were used widely, which included (R-G), (2R-G-B), normalized (R-G)/(G-B), (R/B) (the results as shown in Fig. 2) (Feng *et al.*, 2014; Di Martino and Sessa, 2007; Si *et al.*, 2010). Through comparing and analyzing the corresponding histogram (R-G) color different feature was better for the next step segmentation.

Image segmentation: In the (R-G) color different image segmentation, the traditional OTSU adaptive threshold segmentation had some faults in operation speed (Zhang *et al.*, 2009). Therefore, this study proposed a new algorithm which improved the computing speed and overcome the disadvantages of original algorithm.

Supposing the image size was $a \times b$, if gray value of the pixel (u, v) was $f(u, v)$, then the average gray value of 2D image was:



Fig. 1(a-b): Median filtering, (a) Noise image and (b) Median filtered image

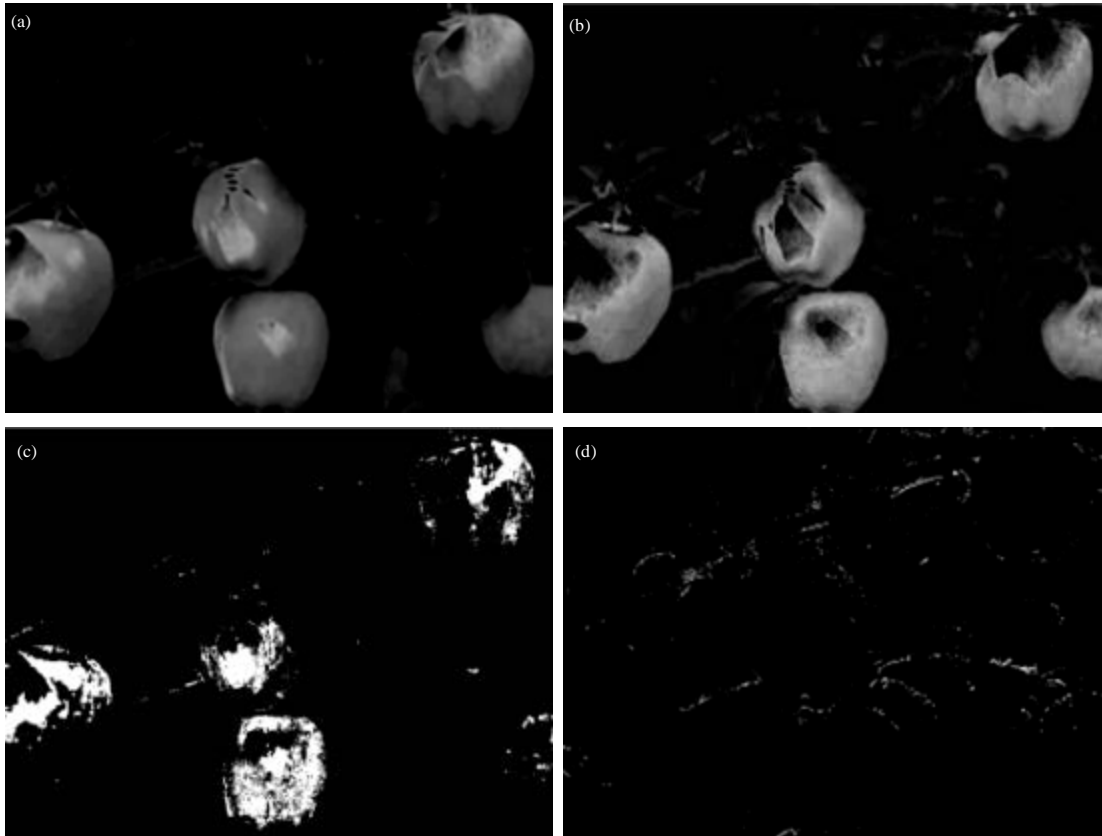


Fig. 2(a-d): Different color information processing results, (a) R-G, (b) 2R-G-B, (c) Normalized (R-G)/(G-B) and (d) R/B

$$T = \frac{\sum_{u=0}^{a-1} \sum_{v=0}^{b-1} f(u,v)}{a \times b} \quad (4)$$

According to T , the image pixels were divided in two classes P_1 and P_2 . In P_1 , the pixel was less than T and in P_2 the pixel was greater than or equal to T . Afterwards, the calculation of pixel average value T_1 and T_2 in P_1 and P_2 respectively, used OTSU algorithm to search the optimal threshold segmentation in the interval $[T_1, T_2]$. This method could reduce the search volume and improve the search speed effectively.

The binary image segmented by improved OSTU algorithm was shown in Fig. 3.

Mathematical morphology processing

Corrosion and expansion: The results of image segmentation (Fig. 3) showed that after the improved OTST algorithm threshold segmentation was used, due to the impact of illumination, branches, leaves and other obstructions, apple image had isolated points and burr, small cracks and other background information that affected the later fruit feature extraction directly. To solve the problem, we introduced mathematical morphology for further processing.

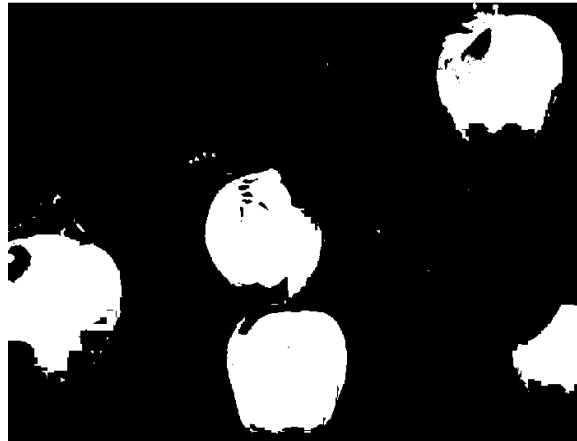


Fig. 3: Binary image segmented by improved OSTU algorithm

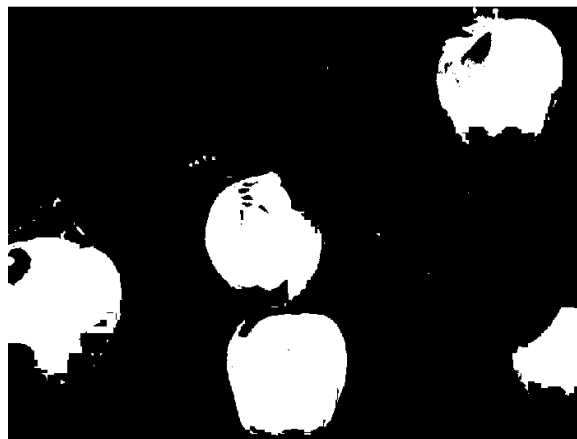


Fig. 4: Image after 2nd corrosion and expansion

According to different image pixels, different pixel structure elements were used in corrosion and expansion processing. This experiment adopted $R = 4$ “disk” circle structure to do 2nd corrosion and expansion. The result was shown in Fig. 4.

If there was larger noise that couldn't be removed after corrosion and expansion, further processing would be taken: Label the regions on the image after being processed morphologically, calculate the area of each region and remove the region whose area was less than $1/6$ maximum area; thus, larger noise points could be eliminated.

Fruit internal filling: Region filling was a solution to the internal hole of fruit, which was intended to fill 0 pixels into 1 within the binary images. In other words, we looked for a pixel in the filled region as a seed, according to the connectivity of the pixel and 0 pixels were filled with 1 constantly to realize regional filling. Supposing α was a 3×3 matrix whose value was 1 and center coordinates were (2, 2), g was a mask and f was a marker, so from f to the reconstruction g could be written as $R_g(f)$. Iterative process definition was as follows:



Fig. 5: Image after region filling

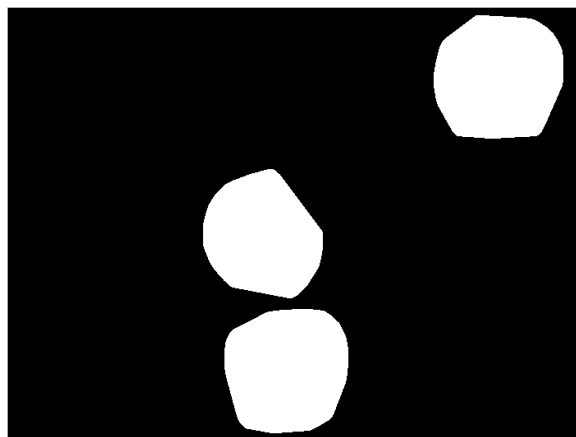


Fig. 6: Pit repairing result image

- Initialized h_1 as the marker image f
- Created structural elements α based on the edge detection precision
- Repeated $h_{k+1} = (h_k \oplus b) \cap g$, until $h_{k+1} = h_k$

Among them, marker f must be a subset of g . The image after region filling was shown in Fig. 5.

Pit repairing: Finding a smallest convex polygon covered the known points on the plane, which was a form of famous minimal covering problem (Bulanon *et al.*, 2002). Therefore, the key to the problem lied in solving the convex hull of plane point set (minimal convex polygon). In this study, firstly we calculated minimal convex polygon in the target region and then filled it with the same pixel values as target region (pixel value in target region was typically 1), so as to achieve the purpose of repairing pits. The procedures above laid the foundation for the next searching for precise position of apple fruit. Figure 6 was the pit repairing result image after the minimal convex

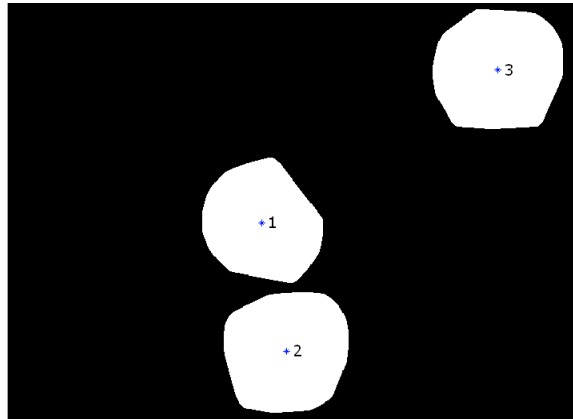


Fig. 7: Centroid acquisition result image

Table 1: Binary connected component centroid coordinates

Characteristic parameter	Centroid coordinate
Connected component 1	(310.090, 277.986)
Connected component 2	(340.075, 440.389)
Connected component 3	(598.346, 84.787)

polygon was drawn in the target region (Fig. 5). Through repairing, fruit with incomplete edge was filtered effectively, so that the extraction of fruit characteristics was closer to the real, complete fruit data.

The original apple image was properly treated, which included color segmentation, morphological filtering, denoising and fruit region filling and repairing and thus the mature fruit region was found. The regions were labeled in the segmented image in order to obtain apple target centroid.

Centroid acquisitions: Centroid feature extraction would impact accuracy of the target location directly, so the accurate extraction of fruit characteristics was the key to realizing the initial positioning (Tan, 2011). As the apple shape was close to sphere, to chose left, right image centroids in each apple as a pair of perfect matching points to simplify the process.

Centroid coordinates (x, y) could be obtained by the following formulae:

$$\begin{cases} x = \frac{1}{S} \sum_{(i,j) \in R} i \\ y = \frac{1}{S} \sum_{(i,j) \in R} j \end{cases} \quad (5)$$

Centroid acquisition of the pit repairing image (Fig. 6) was shown in Fig. 7; the corresponding coordinate values were shown in Table 1.

RESULTS AND DISCUSSION

The experiment selected 100 images that included 307 apples coming from different time, locations and varieties. According to the different growth status, apples were divided into four characteristic:



Fig. 8: Case of different apple growth status

Table 2: Apple recognition results

Parameters	Apple's growth status				Sum
	a(c)	a(d)	b(c)	b(d)	
Number of apple	196.0	32.0	55.0	24.0	307.0
Number of accurate recognition	192.0	25.0	37.0	10.0	264.0
Accurate recognition rate (%)	98.0	78.1	67.3	41.7	86.0

- Without occlusion apple (denoted as a)
- Occlusion apple (denoted as b)
- Apple's color was significantly different from background (denoted as c)
- Apple's color was similar with background (denoted as d)

Four kinds of features were combined into a(c) (without occlusion and background color was different), a(d) (without occlusion and background was similar), b(c) (occlusion and background color was different) and b(d) (occlusion and background was similar).

An example was shown in Fig. 8.

Apple recognition results were shown in Table 2.

The experimental results showed that the total recognition rate reached 86%; in the four types of apple, a(c) recognition rate occupied first place that reached 98%, a(d) and b(c) came second and b(d) was the lowest, only 41.7%.

CONCLUSION

In this study, taking the apple fruit recognition as an example, used (R-G) color feature to identify apple in the natural light based on the characteristics analysis of the study objects. The experiments results showed that the above method could eliminate the shadow, bare soil and so on and the total recognition rate reached 86%. The above algorithm could extract centroid of fruit accurately, which provided the reliable basis for further positioning.

In the process of recognition and segmentation on apple fruit, if the fruit overlaps each other and its color is similar to the background, it is difficult to guarantee fruit target recognition effect and it requires further study.

ACKNOWLEDGMENT

This study was supported by the Department of Science and Technology of Hebei Province (13227422) and the Science and Technology Fund of Hebau (LG201301).

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