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Automatic recognition vision system guided for apple harvesting robot ☆

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ABSTRACT

In apple harvesting robot, the first key part is the machine vision system, which is used to recognize and locate the apples. In this paper, the procedure on how to develop an automatic recognition vision system guided for apple harvesting robot, is proposed. We first use a color charge coupled device camera to capture apple images, and then utilize an industrial computer to process images for recognising fruit. Meanwhile, the vector median filter is applied to remove the color images noise of apple, and images segmentation method based on region growing and color feature is investigated. After that the color feature and shape feature of image are extract, a new classification algorithm based on support vector machine for apple recognition is introduced to improve recognition accuracy and efficiency. Finally, these procedures proposed have been tested on apple harvesting robot under natural conditions in September 2009, and showed a recognition success rate of approximately 89% and average recognition time of 352 ms.

1. Introduction

The challenge of developing a cost-effective robotic system for fruit picking has been taken up by researchers at several places in the world [1–3]. The principal problem required to be solved for a robotic harvesting system is the machine vision system, which affects the robot's dependability and also determines its ability to directly, quickly and accurately recognize the fruit in a real-time [4,5].

In the literature, there are already some results on the research of the harvesting robot vision system. In [6], a review of different vision systems to recognize fruits for automated harvesting was presented, where a model of the attenuation process was presented and used to restore images and derive additional information, which was used to recognize the fruit by color and shape analysis algorithms. Later, the Red–Blue (R–B) chromatic aberration information of the images has been used in [7] to recognize oranges on the tree, and the fruit in the conditions of front lighting and back lighting have also been considered, respectively. In [8], the technology of threshold segmentation and recognition based on hue statistic in Hue-Intensity-Saturation (HIS) color space was researched. Based on the obvious differences of color between the apples and background, Bulanon et al. [9] made use of light and color model to check the Fuji apples, and threshold to segment images. In Ref. [10], a new modified Hue-Saturation-Value (HSV) color space was used to segment images and extract the relevant information of the fruit in the segmentation phase before the localization process. Meanwhile, for images segmentation procedure, a well-known Bayesian classifier for the classification of each pixel as fruit or background was used to classify defects on apples [11]. However, the Bayesian classifier is dependent on a training image to provide information for class mean and the covariance matrix. As can be seen from the literatures above, these methods exist some unsolved disadvantages, such as low accuracy rate, too much time consuming, etc. These disadvantages, to some extent, restrict the real-time and multitask

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ability of the apple harvesting robot operations in a natural environment. To this end, it is necessary to introduce a better fruit recognition method for the apple harvesting robot.

Support vector machine (SVM) is a new pattern recognition method which has been deeply developed in recent years [12,13]. Bases on the principles of minimum frame hazard and kernel functions, this method resolves the inconsistency between complexity and popularization of the model classification efficiently. It also transfers the model recognition problem to a seeking excellent value problem, and assures the value best and overall theoretically. And thus the local constringency phenomenon can be avoided. Especially, the SVM reflects unique advantages and good application foreground in resolving problems such as small samples recognition, nonlinear and high-dimension problems. Consequently, this method has been attracting much attention of the researchers in pattern recognition field [14,15].

Based on the method mentioned above, this paper will try to describe the development of a real-time machine vision recognition system to guide a harvesting robotic for picking Fuji apples in different conditions. By applying SVM, a new recognizing method is developed for improving apple recognition accuracy and efficiency. The outline of the paper is organized as follows. In Section 2, the materials and method of real-time machine vision recognition system is presented. Section 3 reports on a field test result with the apple harvesting robot vision system. And finally, conclusions and suggestions for future research are drawn in Section 4.

2. Materials and methods

2.1. Vision system setup and image acquisition

This robot vision system consists of a VGA (640×480) color charge coupled devices (CCD) video camera with 30 images per second, and an industrial computer with Intel Pentium4 1.7 GHz processor and 512 M memory. CCD video camera is used to acquire original apple images, and the video for windows (VFW) capture technology is adopted to capture the video image. The industrial computer is for dealing with original images and detecting objective, whose software platform is Visual C++ 6.0.

Since the Fuji apples are the most popular in China, our research will focus on this variety. Color images of Fuji apple, which will be examined in the following, are acquired under natural daylight condition on the apple demonstration orchard of Feng Country, Xuzhou City, Jiangsu Province. The color signals from the camera are transferred as a 24-bit red, green, blue (RGB) color image data (640 pixels by 480 pixels in each color band) and processed by an industrial computer.

2.2. Image processing

2.2.1. Image pre-processing

Due to the natural environment and the image acquisition device used, the original unprocessed color apple image inevitably includes noise that influences its quality. In this study, a vector median filter is applied to image enhancement preprocessing [16]. It can not only removes or weakens noise information effectively and highlights the apple fruit in foreground, but also maintains good image edges. The basic process of vector median filter includes three steps. First of all, achieve the average vector $\overline{X}(i,j)$ of all known color image pixel vector $X(i,j)$. Secondly, calculate the distance S_{ij} between $\overline{X}(i,j)$ and $X(i,j)$. Finally, make the S_{min}, which is minimum of the S_{ij}, be the output value of the window central pixel.

In this study, by assuming that the size of original two-dimensional color image setting is $M \times N$ pixel (M is the rows number, N is the columns number), we adopt a vector median filter with a $n \times n$ window to deal with the noise. The arithmetic is as follows.

(a) Take the pixel as a vector $X(i,j)$. By letting $r(i,j)$, $g(i,j)$, $b(i,j)$ be three parameters standing for pixels in RGB color images, then we have $X(i,j) = [r(i,j),\ g(i,j),\ b(i,j)]^T$ $(i = 1, \ldots M;\ j = 1, \ldots N)$.

(b) Calculate the averages of r, g and b, then we get the average vector of the window as

$$\bar{X}(i,j) = [\bar{r}(i,j),\ \bar{g}(i,j),\ \bar{b}(i,j)]^T \tag{1}$$

where

$$\begin{cases} \bar{r} = \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} r(i,j)/n \times n \\ \bar{g} = \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} g(i,j)/n \times n \\ \bar{b} = \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} b(i,j)/n \times n \end{cases}$$

(c) Calculate the distance S_{ij} between each vector and the average vector, and obtain the minimum distance $S_{\min}$ of them.

$$S_{ij} = \|X(i,j) - \bar{X}(i,j)\| \tag{2}$$

(d) Make the pixel $barX_{\min}$ corresponding to $S_{\min}$ as the vector median of the window, then let it replace the central pixel vector of the window.

In our study, the size of original color image setting is 640 × 480 pixel. Vector median filter of color images with the $n \times n$ window being 3 × 3, is adopted to carry out enhancement for the apple color image. The image filter result is shown in Fig. 1. It can be shown that vector median filter of color images can wipe off noise efficiently, and stand out the apple fruit in foreground. Furthermore, the solution can keep the edge and detail. In additional, the window central pixel is replaced by the pixel corresponding to minimum distance, while not replaced by the synthetical vector. And thus the color feature will remain unchanged.

2.2.2. Image segmentation

Most apple images acquired in the natural conditions usually include branches and leaves which complicate matters. By only using the conventional image segmentation algorithm, it is difficult to achieve the desirable result. The seeded region growing method and color feature are employed here to develop an image segmentation algorithm for identifying apple fruit from complex background.

The segmentation effect of seeded region growing is determined by the selection of initial seed point and the growing rules. In this study, the images are colorized in RGB model. First, we map the image pixels into column diagram of RGB model. Then, select some pixel as the preparative growing seed in these colors whose probability is the biggest. After that, according to [17,18], we tentatively select the 5 × 5 pixel region of the preparative seed, and set a threshold value, then calculate the number of pixels which are less than the threshold value. If the number of pixels is more than 20, we regard the region around these pixels as the goal object, namely the apple fruit. If the number is less than 20, we consider that the preparative seed picks some isolated points whose color is close to that of the object. Then, we abnegate this preparative seed and choose a new one. Finally, we select a growing seed to grow it under the growing rules.

The growing threshold value obeys the following rules: the color of growing seed color is just the main color of the apple fruit. Thus, we can choose the absolute value as the threshold, which is the difference between the color of the growing seed and the average value of the whole image. In this study, the difference between the color of apple fruit and background is distinct, so we can select a bigger value as the threshold one.

The growing rules, which are the key ingredient, determine the dependability and running time of the region growing algorithm. In this study, we investigate 8 neighbor pixels starting from the growing point. If the color difference between growing point and that of the central point is less than the threshold value, then we add this pixel to the growing region. After that, the central point is labeled. Whether label or unlabel its neighbored pixels is according to their color homogeneity. Do the same procedure to the neighbor pixels' neighbor pixels iteratively until no homogeneity pixels can be found.

For a color image, to judge whether the colors are homogeneous or not can be measured by the Euclid distance. It means that there are two pixels P_1 (r_1,g_1,b_1) and P_2 (r_2,g_2,b_2) in RGB model, and their distance is

$$d(P_1,P_2) = \sqrt{(r_1 - r_2)^2 + (g_1 - g_2)^2 + (b_1 - b_2)^2} \tag{3}$$

Based on the method proposed above, we can divide the apple fruit image into two parts including fruit and background. The segment image is used to extract features. However, during the process of segmenting, the isolated dots, burrs and holes are usually exist in the image. To decrease the influence of these noises for subsequent image recognizing steps, we adopt opening and closing operations in mathematical morphology to remove the noises. The concrete process is to adopt the

(a) The original image (b) Image after filtering

Fig. 1. Results of vector median filter applied apple color images.

open-shut filter sequence for executing the task iteratively. At the beginning, the opening operation is utilized to clear the isolated dots and burrs. Nextly, the closing operation is applied to fill up the small holes. And then, we can obtain the ideal image. The segmentation and mathematical morphology operation results of apple image are shown in Fig. 2.

2.2.3. Image feature extraction

2.2.3.1. Apple image color feature extraction. The images are taken from the apple tree under natural daylight conditions. Four lighting conditions are investigated: (a) front lighting, (b) back lighting, (c) fruit in the shade, and (d) cloudy. Here, conditions (a), (b) and (c) are taken under sunny weather. Changes in lighting condition result in different quality images, and affecting subsequent image processing steps [9]. Therefore, it is necessary to choose a color model which can fit most lighting conditions. The HIS color model is a common color perceptive model, which describes color with its three components of H, I and S. Note that the chromaticity is hardly influenced by the lighting conditions. Here, we use the H and S components of HIS model to deal with this problem.

Compared with the RGB model, the HIS model is easier for one perceiving the colors, and also accords with people's habits to describe colors. This model is based on two important facts: (a) the component of I does nothing with the color information of image; (b) the chroma components of H and S have close relation with people manner to perceive colors. The well-known non-linear transformation from RGB components to the HIS color model is employed as follows [19]

$$\mathrm{H} = \begin{cases} \theta, & \mathrm{G} \geqslant \mathrm{B} \\ 2\pi - \theta, & \mathrm{G} < \mathrm{B} \end{cases} \tag{4}$$

$$\theta = \cos^{-1}\left[\frac{0.5[(\mathrm{R}-\mathrm{G}) + (\mathrm{R}-\mathrm{B})]}{\sqrt{(\mathrm{R}-\mathrm{G})^2 + (\mathrm{R}-\mathrm{B})(\mathrm{G}-\mathrm{B})}}\right] \tag{5}$$

$$\mathrm{S} = 1 - \frac{3}{(\mathrm{R}+\mathrm{G}+\mathrm{B})}[\min(\mathrm{R},\mathrm{G},\mathrm{B})] \tag{6}$$

$$\mathrm{I} = \frac{1}{3}(\mathrm{R}+\mathrm{G}+\mathrm{B}) \tag{7}$$

In view of the varieties of the light intensity, the influence of the light and shade in the image should be avoided. The components of H and S which do nothing with lightness are chosen to extract image features. Each point in the HIS colors space of apple fruit image can be regarded as a point in three-dimensional space of HIS model. Therefore, the difference of two colors can be measured by the Euclid distance of two color points. The chromatic aberration formula is as follows

$$\Delta E = \sqrt{(\Delta H)^2 + (\Delta S)^2} \tag{8}$$

By this way, the colors can be compared directly in HIS color space, and the color and intensity information can be controlled well. Moreover, it is efficient in distinguishing small difference of the colors. And thus, H and S components in HIS color space are employed to recognize the color feature.

2.2.3.2. Apple image shape feature extraction. The shape feature is important in object recognition. Different kinds of objects have great differences in shape [5]. In this study, apple fruit, branches and leaves have themselves specific shapes, and their

(a)The original image (b) Mathematical morphology operation results

Fig. 2. Segmentation and mathematical morphology operation results of apple fruit images.

differences in shape are significant. So, according to the edge of apple fruit, the shape feature used in following classified process, can be extracted.

The biggest character of objects geometry shape is that they are not changed with the change of the objects position, size and angle in image. Consequently, we should extract the feature vectors that can satisfy RST (round, scale, transfer) invariability. In all the features of apple, feature parameters of round variance, ellipse variance, tightness, and ratio of perimeter and square area can describe furthest the outline feature of apple efficiently, so the above four feature parameter vectors are extracted for further research. The extraction process detailed can be described as follow.

2.2.3.2.1. Reckon image outline position. Outline position, namely, position of boundary pixels in image, can be obtained by edge detection method such as Soble or Robert arithmetic operators [19]. Assuming the outline edge coordinate is $p_i = [x_i, y_i]^T$, the outline is a setting P of N stochastic vectors, $P = \{p_i\}, i = 1, 2, \ldots, N$. The average vector is μ, namely, the object centroid coordinate is

$$\mu = \frac{1}{N}\sum_{i=1}^{N} p_i \tag{9}$$

The average radius μ_r is

$$\mu_r = \frac{1}{N}\sum_{i=1}^{N} |p_i - \mu| \tag{10}$$

2.2.3.2.2. Calculate parameters of outline region area and perimeter. Assuming A is the outline region area of image, which is the summation of the numbers of region pixels. S_o is the region perimeter. The way to calculate S_o is as follows. In the boundary pixels of the region, we suppose the distance between some pixel and another one that lies up, down, left or right, is 1, and the distance between it and another one lying slanting position is $\sqrt{2}$. Then S_o is the summation of these distances.

2.2.3.2.3. Extract feature parameter vectors of the round variance, ellipse variance, tightness, ratio of perimeter and square. Round variance σ_c reflects the resemblance extent between the outline of object and the round. The smaller σ_c indicates the more chance of the object to be the round. It is defined as

$$\sigma_c = \frac{1}{N\mu^2}\sum_{i,r=1}^{N} (\|p_i - \mu\| - \mu_r) \tag{11}$$

Ellipse variance σ_e reflects the resemblance extent between the outline of object and the ellipse whose principal axis is axis, the smaller σ_e indicates the object is more like an ellipse. This value is applied when the apple fruit image is influenced by noise, and the fruit image cannot take on an absolute round. It is defined as

$$\sigma_e = \frac{1}{N\mu_{rc}}\sum_{i=1}^{N} \left(\sqrt{(p_i - \mu)^T C^{-1} (p_i - \mu)} - \mu_{rc}\right)^2 \tag{12}$$

where $\mu_{rc} = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(p_i - \mu)^T C^{-1} (p_i - \mu)}\right)$.

Assuming C_o is the tightness of the object, the smaller value reflects that the composition of object is more incompact. It is defined as

$$C_o = \frac{2\sqrt{A\pi}}{S_o} \tag{13}$$

The ratio of perimeter and square area D is defined as

$$D = S_o^2/A \tag{14}$$

These features are regarded as the eigenvectors of each sample, which will be employed to the following training and classification.

2.3. Apple automatic recognition based on SVM

2.3.1. Support vector machine

SVM is a learning system that uses a hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory [13]. It includes linear separable question and non-linear separable question. The reader is referred to [12] for a more comprehensive introduction.

2.3.1.1. Linear separable question. For binary linear separable classification, the basic thought of SVM is to find an optimal hyperplane between the two kinds of examples setting to classify them and make their distance furthest. For example, in Fig. 3, solid dots and hollow loop stand for the first and the second training examples, respectively. H is the optimal hyperplane, H1 and H2 are parallel with H. The points on H1 are the first samples whose distance to H are the shortest, and the

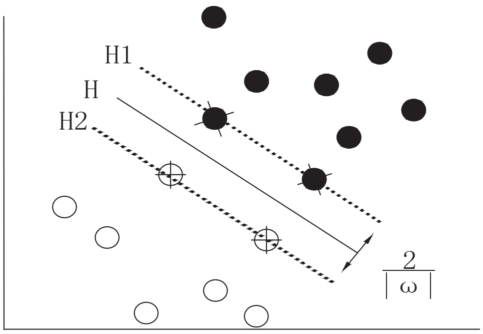


Fig. 3. The sketch of two-dimensional linear separable optimal hyperplane.

points on H2 are the second samples whose distance to H are the shortest too. The points on H1 and H2 are on the edge of isolation belt, and these examples are called support vectors. They determine the isolation belt. In this study, the classified judged function is selected as follows.

$$f(x) = \mathrm{sgn}((\omega^* \cdot x) + b^*) = \mathrm{sgn}\left(\sum_{i=1}^{N} a_i^* y_i (x_i \cdot x) + b^*\right) \tag{15}$$

where the coefficient a^* is the Lagrange multiplier and b^* is the classification threshold.

2.3.1.2. Non-linear separable question. An important advantage of SVM is to deal with non-linear separable question. When the question is non-linear separable, the feature mapping method can be adopted. It can map the non-linear separable feature vector space to a high dimensional feature space which is linear separable. Then, the examples are classified based on linear separable SVM.

The principle map of feature mapping method is shown as in Fig. 4. Fig. 4(a) shows two kinds of non-linear separable examples in the original feature space, and Fig. 4(b) shows the result of non-linear separable question mapping into linear separable question. The feature mapping method is fulfilled by using kernel functions, which can complete the transform from the non-linear separable question to a linear separable one. Certainly, the results of classification are different when different kernel functions are adopted. The three kernel functions that are usually used as follows [12]

(1) Poly kernel function

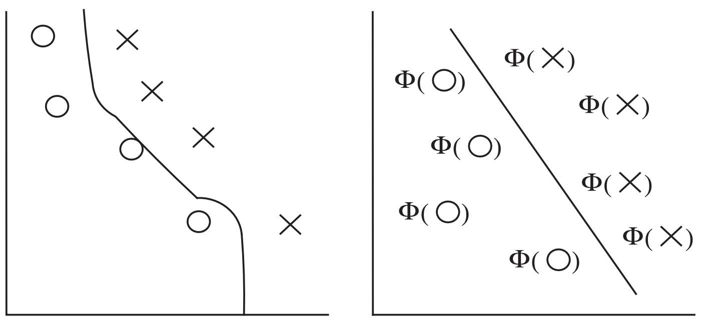
$$K(x, x_i) = ((x \cdot x_i) + 1)^q \tag{16}$$

(2) Radial Basis Function (RBF) kernel function

$$K(x, x_i) = \exp\left(-\frac{|x - x_i|^2}{\sigma^2}\right) \tag{17}$$

(3) Sigmoid kernel function

$$K(x, x_i) = \tan h(\alpha(x \cdot x_i) + \beta) \tag{18}$$



(a) Non-linear separable question (b) linear separable question after mapping

Fig. 4. Non-linear separable question mapping to linear separable question.

2.3.2. Recognition of apple fruit based on SVM with color feature and shape feature

Select 150 Fuji apple images as a training set, and establish a recognition model. Then, select another 50 apple images as a testing set, which is used to validate the dependence of the model. In the experiment, each apple color image is pre-processed, segmented and extracted for features, and then recognized based on SVM. In allusion to feature data of the apple fruit image, SVM is classified and tested by different kernel functions to distinguish whether SVM has different classification capacity or not and to confirm which kind of SVM is much fitter for the apple fruit recognition.

When recognizing an apple manually, the red pericarp (*viz.* color information) and round fruit (*viz.* shape information) are shown. So firstly, SVM based on only color feature or shape feature is used in apple recognition, respectively. And then we use SVM based on both color feature and shape feature to recognize apple. The three recognition simulated experiments are contrasted and discussed in following subsections.

2.3.2.1. Recognition of apple fruit based on color feature. In the recognition experiment based on color feature, the color features of the apple fruit image are extracted after pre-processing. The sample set and testing set are recognized by three different kinds of SVM kernel functions, and then their identification capabilities are compared. In SVM algorithm, we choose penalized coefficient $C = 1$, slack variable $\xi = 0.001$, and $q = 3$ in Poly kernel function, $\sigma^2 = 3/2$ in RBF kernel function, $\alpha = 3$, $\beta = -10$ in Sigmoid kernel function. The results are showed in Table 1.

2.3.2.2. Recognition of apple fruit based on shape feature. In the recognition experiment based on shape feature, every image pre-processed and segmented, is classified and experimented after shape feature are extracted integrated with SVM. Here, we choose $C = 1$, $\xi = 0.001$, and $q = 2$ in Poly kernel function, $\sigma^2 = 1$ in RBF kernel function, $\alpha = 1/3$, $\beta = -1$ in Sigmoid kernel function. The results are showed in Table 2.

2.3.2.3. Recognition of apple fruit based on color feature and shape feature. In the recognition experiment based on both color feature and shape feature, by using SVM for apple fruit image, we take $c = 1$, $\xi = 0.001$; $q = 3$ in Poly kernel function; $\sigma^2 = 6$ in RBF kernel function and $\alpha = 1/6$, $\beta = -1$ in Sigmoid kernel function. The results are showed in Table 3.

As shown in the three tables above, we can find that apple fruit recognition based on only color feature or shape feature is inferior to that integrated both of them, either in the aspect of recognition accurate rate or running time. The RBF function is the one with the highest recognition accurate rate in the three SVM functions. The Sigmoid function has the shortest running time, but its recognition rate is the lowest. The other functions are almost the same in running time. By taking into account all the factors mentioned above, we can conclude that the SVM method with RBF kernel function based on both color feature and shape feature is the best for apple recognition.

Table 1
Recognition results of apple fruit based on color feature.

Result	Method SVM		
	Poly	RBF	Sigmoid
The average of recognition rate (%)	62.3	89.1	58.5
Running time (ms)	283	247	212

Table 2
Recognition results of apple fruit based on shape feature.

Result	Method SVM		
	Poly	RBF	Sigmoid
The average of recognition rate (%)	82.9	90.1	69.2
Running time (ms)	262	253	171

Table 3
Recognition results of apple fruit based on color feature and shape feature.

Result	Method SVM		
	Poly	RBF	Sigmoid
The average of recognition rate (%)	85.7	93.3	57.2
Running time (ms)	268	256	175

3. Field test results and discussion of apple harvesting robot vision system

The apple harvesting robot developed independently by ourselves is shown in Fig. 5. The automatic recognition vision system for apple proposed above is applied to guide robot for picking. In the sequel, the results of the two experiments for apple recognition are presented in terms of the success rate and execution real-time. The experiment was done in September 2009 at Demonstration Orchard of Changping, Beijing.

Fig. 5. The harvest robot in apple demonstration orchard during the field test.

(a)Apple orchard scene in natural outdoor

(b) Red apple recognition result under front lighting

(c) Red apple recognition result under back lighting

(d) Red apple recognition result with protected bag

Fig. 6. Apple automatic recognition result based on SVM under different conditions.

Table 4
Images recognition time.

Image frame	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Recognition time (ms)	235	235	315	390	315	310	390	390	310	390	390	310	390	310	235	315	390	390	310	390	390	390	315	390	395
Image frame	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
Recognition time (ms)	310	390	390	310	315	390	390	315	310	390	390	310	390	390	310	390	390	310	315	390	315	310	390	390	390
Image frame	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
Recognition time (ms)	315	390	395	310	390	390	310	315	390	390	315	310	390	390	310	390	390	310	390	390	31	315	390	395	310
Image frame	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
Recognition time (ms)	315	390	310	315	390	395	310	390	390	310	390	390	310	315	390	390	310	315	390	390	315	390	390	315	390

3.1. Recognition success rate

In different orchard, the apple variety is usually different, and so does the apple color. Furthermore, with the difference of planting areas, the protected measures for apple are also different. To validate the availability for the method mentioned above, these factors have been considered in the recognition algorithm experiments for the machine vision system. Also, in order to meet with visibility, the recognized apple is labeled by symbol "+". Meanwhile, the obscured apple by leaves, branches, or overlapped with other apples are not labeled with any symbol.

Fig. 6 shows the apple automatic recognition results under different conditions. The sample image Fig. 6(a) shows apple orchard scene taken under natural outdoors. The lowest height of the apples in tree is 1 m above the ground. The interval distance of two rows tree is about 5 m. Thus the apple harvesting robot can perform apple searching, recognizing and picking smoothly according to designated path. Fig. 6(b) shows red apple recognition result without protected bag under front lighting. Here, 13 apples have been recognized. The error rate is almost zero. Fig. 6(c) shows red apple recognition result under back lighting. Approximately 89% of the fruit is successfully detected. Fig. 6(d) shows red apple recognition result with protected bag. There, 7 apples with protected bag have been recognized accurately, and only 2 apples cannot be detected. Foliage occlusion caused nondetection cases. The experiment results show that the developed method is effective, and thus could be applied to exactly recognize apple under different conditions.

3.2. Recognition execution real-time

In recognition execution real-time experiment, 100 frame dynamic video images (320 pixels by 240 pixels) are acquired continuously by the CCD video camera. The apple recognition algorithm is implemented using Visual C++ 6.0. Table 4 gives the recognition time of each frame image. The average recognition time of 100 frame images is 352 ms. From these results, it can be concluded that the developed algorithm can be used to guide a robot manipulator as it approaches the apple in real-time.

4. Conclusions

A real-time vision recognition system to guide a harvesting robotic for apple picking in different conditions is developed. Firstly, the apple fruit images acquired by CCD camera are pre-processed by vector median filter. Then, segmentation method based on seeded region growing method and color feature is applied, and color feature and shape feature of color image are extracted. After that, a new classification algorithm based on SVM for recognition of apple fruit is developed to improve recognition accuracy and efficiency. Simulation experiment indicates that the recognition rate of the apple based on SVM of color and shape feature is higher than that of only using the color or shape feature, and the running time is also shorter. This machine vision system described has been tested on apple harvesting robot under natural conditions in September 2009, and it is successful in recognizing the apples under different conditions. Approximately 89% of the fruit are successfully detected. The average recognition time is 352 ms. In general, the machine vision system meets the requirement of apple harvesting robot for the recognition accuracy rate and time efficiency. However, nondetection case caused by the foliage occlusion has an average error rate of 11%. Future work will be performed on this area to minimize unrecognition of apples. In addition, reducing the recognition execution time is still a challenge, since it is too high to allow this algorithm to be implemented in a real-time system.

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