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Recognition Algorithm and Optimization Experiments on Tomato Picking Robots

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Abstract

In order to improve the recognition accuracy of vision system on tomato picking robots, the paper proposed a method of feature extraction and recognition for ripe tomato based on illumination irrelevant images and support vector machine (SVM). In this method, we adopted vector median filter (VMF) to process the tomato images to eliminate noise and make the images more smooth firstly. To avoid the effects of natural environment illumination to the vision system, we processed tomato images and obtained the tomato illumination irrelevant images according to color constancy algorithm of the single pixel. Secondly, we segmented illumination irrelevant images using OSTU method, separated multiple objects by a watershed algorithm based on distance transform and got the target area with mathematical morphology. Also we extracted color, shape and textural features of the ripe tomatoes. Finally, we did experiments on recognizing tomatoes using support vector machine (SVM) with different kernel functions. At the same time, in order to obtain optimal model of SVM, we adopted cross validation and grid search method to optimize the model parameters. The experiment results show that illumination irrelevant processing not only can eliminate the influence of light intensity, but save a gray transferring step for further image segmentation. SVM with radial basis function is better than other kernel functions SVM and the tomato recognition accuracy is 95.7%. Through optimizing the parameter C and r of radial basis function, the tomato recognition accuracy reaches up to 96.9% with the increase of 1.2% when C and r is 4 and 16 respectively. This proves that it's feasible and effective to optimize SVM's parameters by cross validation and grid search method, which provide foundation for further research on vision system of tomato picking robots.

Keywords: *Illumination irrelevant images; Recognition; Support vector machine; Feature extraction*

1. Introduction

Fruit harvesting is very important process in agricultural production, which affects the production efficiency, quality and post-harvest storage of fruits, *etc*. In addition, harvesting is a seasonal and labor-intensive task. To improve the production quality and reduce harvesting burden, many kinds of harvesting robots have been studied in recent years, such as tomato, strawberry and apple harvesting robots, *etc.*, [1-3]. The vision system is one of important components of the harvesting robot. It's the key technology for the robot vision system to recognize and locate the fruits fastly and accurately in natural environment, which affects the robot's working efficiency and reliability directly [4]. There are many methods to recognize targets, in which supporting vector machine (SVM) algorithm shows obvious advantages in solving the small sample, nonlinearity, multi-dimension and local minima problems. Scholars of the world have carried out a lot of researches on the application of SVM and proposed various improved methods. H. Q. Wang *et. al.*, studied cucumbers image recognizing using least squares SVM, and the rate

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of recognition is 82.9%, which can be used for complex background by combining with a pulse coupled neural network [5], but it always takes a long time to find the targets. H. Y. Wang *et. al.*, combined genetic algorithm with SVM to design multi-class SVM classifier for classifying corn varieties, and the accuracy rate of recognition is 95.9% [6]. Y.X. Hu *et. al.*, did researches on 9 varieties of harmful pests recognizing in the stored grain based on simulating annealing – SVM algorithm, and the recognition rate was 95.56% with the rapid recognition speed [7]. Y. X. Pu *et. al.*, optimized SVM's feature subset by dual-coding genetic algorithm, and used for identify crop pests image, which greatly reduced the number of feature vectors and improve the recognition accuracy rate [8]. In SVM optimization, G. Chen proposed a model parameter adaptive optimization algorithm for SVM based on genetic algorithms, and the recognition rate reached 90.8% with the optimized model [9]. L. Liu *et. al.*, optimized SVM parameters based on artificial bee colony algorithm, which overcome the problem of local optimal solution, and obtained high correct classification rate and running speed [10]. Meanwhile, many scholars in other fields have carried out researches on identification and location technology for apples, citrus, eggplant, tomatoes and other fruits [11-16], and achieved remarkable results.

In this paper, to improve tomato harvesting success rate, we have done some researches on recognition of ripe red tomatoes planted in the vegetable greenhouse based on SVM with different kernel functions. In the experiments, illumination irrelevant processing for tomato images have been done to eliminate the influence of light and illumination invariant images were obtained. To improve the recognition accuracy rate of the vision system, we optimized parameters of SVM model using cross-validation and grid search method.

2. Illumination Irrelevant Processing for Tomato Images

Tomatoes always grow in the natural environment, so the light source direction, the shooting distance and light intensity *etc.*, would change real information of tomato fruit images and affect the recognition accuracy of the vision system. To eliminate the effects of light intensity, we have conducted illumination irrelevant processing for the tomato colorful images after median filtering by a single pixel color constancy algorithm [17], and got tomato fruit illumination images.

It needs the following three conditions for getting illumination irrelevant images: the processed image is based on the Lambertian model; illumination source is Planck; ideal camera narrowband response. Then every *RGB* components of an image pixel can be expressed as:

$$\rho_k = \sigma \int E(\lambda) S(\lambda) Q_K(\lambda) d\lambda \quad k = R, G, B \tag{1}$$

Where ρ is *R*, *G*, *B* value of the corresponding pixel; σ is Lambertian shading coefficient , a constant; $E(\lambda)$ is light spectrum power distribution; $S(\lambda)$ is surface reflectivity of the object; $Q_K(\lambda)$is the frequency sensitivity of the camera to *R*, *G*, *B* component of a pixel; λ is wavelength of light with different color, nm.

If the camera is narrow wide response, we can get $Q_K(\lambda)=\delta(\lambda-\lambda_K)$, δ is the Dirac function, then

$$\rho_k = \sigma \int E(\lambda) S(\lambda) \delta(\lambda - \lambda_k) d\lambda = \sigma E(\lambda_k) S(\lambda_k) \tag{2}$$

Under Planck light conditions, Wien approximation is conducted based on Planck theorem, the simplified Planck equation is:

$$E(\lambda, T) \approx I c_1 \lambda^{-5} \exp(-\frac{c_2}{T\lambda}) \tag{3}$$

Where c_1 and c_2 are constant, I is the light source intensity, cd; T is color temperature of blackbody radiator, K. Thus, the color value of a single pixel can be written as:

$$\rho_k = \sigma I c_1 \lambda_k^{-5} \exp(-\frac{c_2}{T\lambda_k}) S(\lambda_k) \tag{4}$$

Defined two-dimensional wave band ratio vector as:

$$\chi_j = \frac{\rho_k}{\rho_p} \quad k \in \{R, G, B\}, \quad k \neq p, \ j = 1,2 \tag{5}$$

From Equation (4) and Equation (5), we can obtained

$$\chi_j = \frac{\lambda_k^{-5} \exp(-\frac{c_2}{T\lambda_k}) S(\lambda_k)}{\lambda_p^{-5} \exp(-\frac{c_2}{T\lambda_p}) S(\lambda_p)} \tag{6}$$

From Equation (6), we can see that wave band ratio vector χ has been affected by light intensity I and Lambert shadow coefficient σ.

The direction angle of the band ratio vector χ is defined as θ, then information entropy of gray images change with the θ values. Information entropy shows how much information contained in an image. Therefore, the smaller the entropy of light irrelevant image is, the more obvious the effect of eliminating light is, so θ is called the light irrelevant angle. In this paper, we calculated the entropy of gray images when θ traverses from 0 to 180 degree using the minimum entropy criterion. The entropy value curve is shown in Figure1. It shows that the illumination irrelevant angle of the camera used in this paper is about 120°.

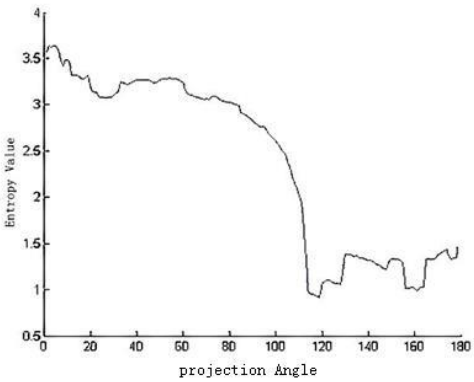
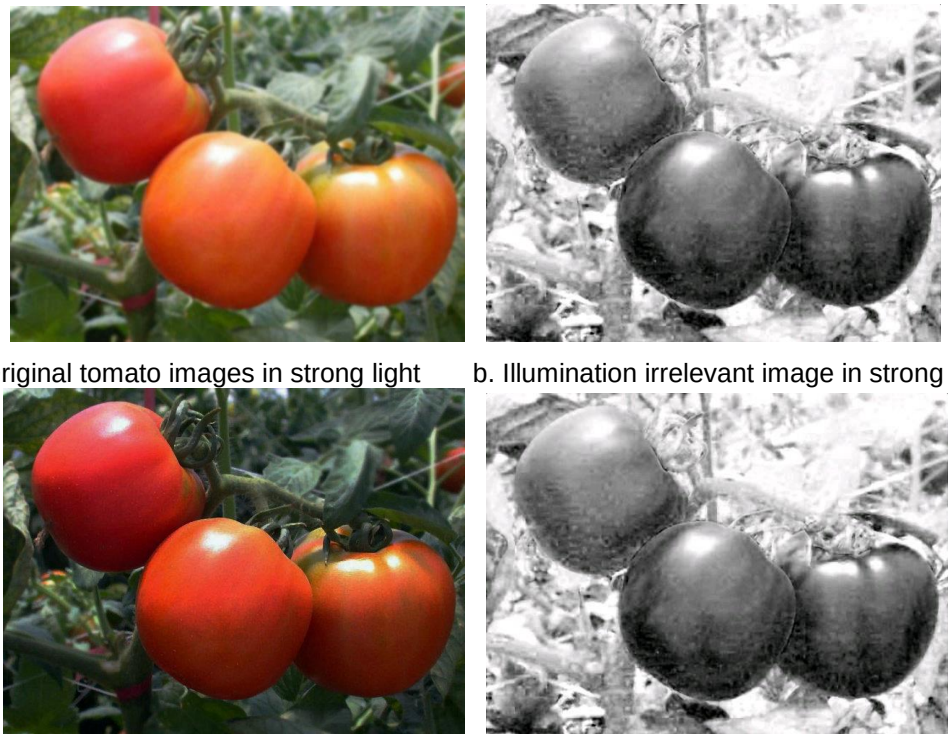


Figure1. Entropy Value Curve

In the experiment, we took pictures of ripe red tomatoes cultivated in vegetable greenhouse at 9:00 to 11:00 a.m. and 16:00 to 18:00 p.m. from July to August in 2014, and the taking distance is 300 mm to 1000mm by NIKON COOLPIX S2600. We chose four light conditions during taking pictures, such as the strong light, the weak light, facing light and backlight. Illumination irrelevant images in the strong and weak light were obtained by illumination irrelevant processing, shown in Figure 2. It indicates that there is no difference in the tomato illumination irrelevant images acquired from the strong and weak light. Therefore, illumination irrelevant processing not only eliminates the influence of light intensity of tomato growing environment, but transforms the original color images into gray images, which can save a step of the gradation conversion for later image

segmentation and improve the processing speed. In addition, the processed image can provide clear tomato fruit area and contour for further studying.



a. Original tomato images in strong light b. Illumination irrelevant image in strong light

c. Original tomato image in weak light d. Illumination irrelevant image in weak light

Figure 2. Tomato Fruit Images and Their Illumination Irrelevant Images

3. Image Segmentation and Multi-Object Extraction

Due to there are always several tomato fruits growing in one cluster together simultaneously, to solve adjacent fruits covering each other, we segmented the tomato fruits and background using maximum class square error (OTsu) method [18], then successfully achieved multiple objects separation by a watershed algorithm based on distance transform and extracted the colorful target area of each fruit.

To reduce the amount of calculation, a serial scan transformation method is adopted in the distance transformation. In this method, the forward scanning and the inverse scanning for images are needed. During the forward scanning, the distance transform of the upper-left neighborhood is completed by 4-neighborhood transform for each pixel. The forward scanning mathematical formula is expressed as

$$S_{i,j} = \begin{cases} 0 & f_{i,j} = 0 \\ \min\{(S_{i,j-1}+1),(S_{i-1,j}+1)\} & f_{i,j} = 1 \end{cases} \tag{7}$$

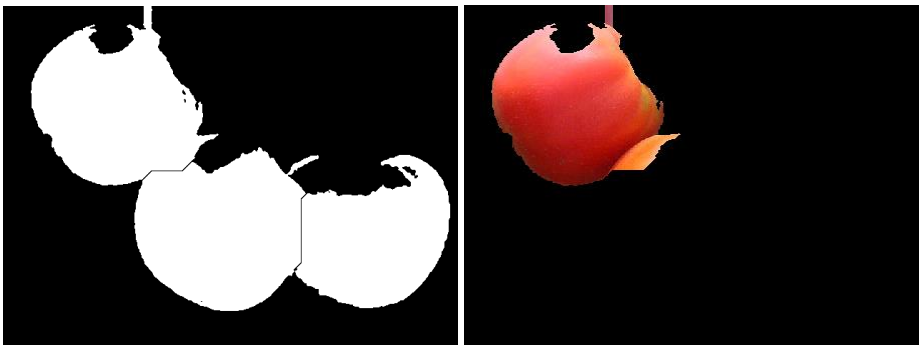
Where $f_{i,j}$ is the pixel value of original images, $S_{i,j}$ is the distance transform results during forward scanning.

In the inverse scanning, the distance transform is conducted for the lower right neighborhood. Then, the distance transform results obtained in the inverse scanning are compared with that of the forward scanning. The mathematical formula of the inverse scanning is expressed as

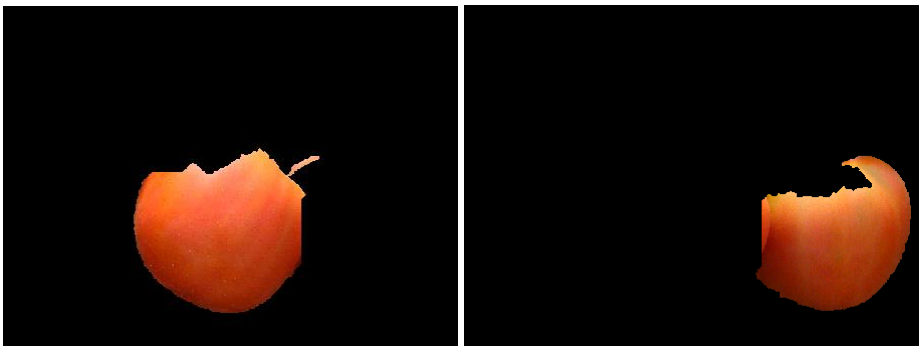
$$D_{i,j} = \begin{cases} 0 & S_{i,j} = 0 \\ \min\{(D_{i+1,j}+1),(D_{i,j+1}+1),S_{i,j}\} & S_{i,j} \neq 0 \end{cases} \tag{8}$$

Where $D_{i,j}$ is the final distance transform results in the inverse scanning.

Tomato image segmentation and Multi-target extraction is shown in Figure 3. Figure 3a, shows that multiple target tomato images are divided successfully by watershed algorithm based on distance transform, and each tomato target contour is clear. From Figure 3b, c, d, we can see that the target area of each tomato colorful image is extracted by marking the connected area of targets, and shape and contours of each tomato is approximately complete, which lays the foundation for later feature extraction.



a. Target Segmentation Image b. Target Extraction 1



c. Target Extraction 2 d . Target Extraction 3

Figure 3. Tomato Image Segmentation and Multi-Target Extraction

4. Feature Extraction of Tomato Images

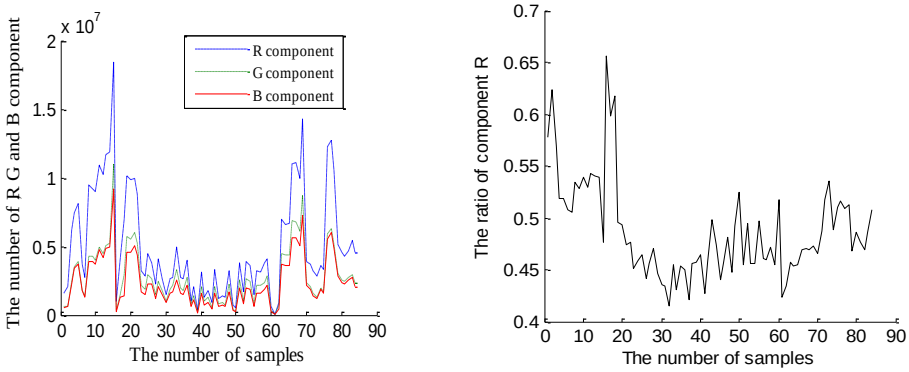
4.1. Color Feature Extraction

Color feature extraction is to extract *R*, *G* and *B* component values of tomato images respectively in the *RGB* color space. According to the statistical analysis, the *R* component pixel value of ripe red tomato image is greater than that of the *G* and *B* component, so color feature value is defined as the sum of all the *R* component pixel values divided by the sum of *R*, *G* and *B* component pixel values, namely

$$E = \frac{\sum P_R}{\sum P_B + \sum P_G + \sum P_R} \tag{9}$$

Where *E* is the color feature ratio, P_i is the *i* component pixel value of tomato images (*i* is *R*, *G* and *B*).

In this paper, we chose 84 target area samples from tomato segmentation images which background was removed. The statistics and verifying results of tomato images are shown in Figure 4. It indicates that the pixel value sum of *R* component is greater than that of the *G* and *B* components, and the color characteristic ratio of the *R* component is from 0.42 to 0.62, which proves that the color feature ratio *E* is valid to the red fruit.



a. the *R*,*G* and *B* component Statistics b. the ratio of component *R*

Figure 4. Color Component Statistics of Tomato Images

4.2. Shape Feature Extraction

Ripe tomato fruit, branches and leaves have different shapes. According to recognition theory, the geometric shape of an object has the characteristics of *RST* (*i.e.*, Rotation, Scaling and Translation), That is, the geometric shape feature of an object won't change with position, size and rotation angle of the image [19]. In this paper, circular variance, dispersion and elongation were adopted as the shape features.

Circular variance represents similarity degree between the object shape and circle. The smaller the circular variance value is, the more close to a circle the object shape is. Circular variance can be written as

$$\omega = \frac{1}{N\mu_r^2}\sum_{i=1}^{N}\left(\left\|p_i - \mu\right\| - \mu_r\right)^2 \tag{10}$$

Where ω is Circular variance, N is the number of edge pixels, p_i is an edge pixel coordinates in the image coordinate system, u is the centroid coordinates of objects, μ_r is the average radius of a target, mm.

Dispersion is expressed as

$$D = \frac{L^2}{A} \tag{11}$$

Where, D is the dispersion, L is the perimeter of the tomato contour, mm, A is the area of the tomato fruit, mm^2.

The formula of elongation is defined as

$$S = H/W \tag{12}$$

Where, H and W are the length and width of the minimum exterior rectangle of target area respectively, mm.

4.3. Texture Feature Extraction

Texture feature is a value obtained through quantifying the internal features of gray level of an object, which indicates the spatial distribution regular of the pixel gray level. In general, the texture feature is affected by the position, direction, size and shape, not by average gray level (*i.e.*, brightness) [20].

In this paper, Texture feature of tomato image was extracted based on Gray-Level Co-occurrence Matrix method (GLCM) [21]. This method is simple and has strong adaptability and robustness. The angular second moment, contrast ratio and entropy *etc.*,

can be got according to GLCM during texture feature extracting. Angular second moment can be expressed as

$$ASM = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left[P(i,j)\right]^2 \tag{13}$$

Angular second moment can measure the distribution uniformity of the image gray-level. It indicates that the image pixel gray distribute much uniformly in the local area when GLCM elements centralize on the main diagonal. For the whole image, the texture is coarse when angular second moment is greater. Conversely the angular second moment is smaller.

In the feature extracting experiment, we took 240 training images and 110 testing images of tomato fruits under different conditions, and extracted 853 training samples from training images and 477 testing samples from testing images respectively. Parts of the feature vector data is shown in Table 1.

Table 1. Parts of Feature Vector Data

Samples	Color feature value	Circle variance	Dispersion	Elongation	Angle second moment
1	0.4582	0.0331	11.6000	0.8500	0.8037
2	0.5629	0.0653	21.0300	0.9070	0.8512
3	0.4555	0.1419	15.3200	0.8514	0.8632
4	0.6174	0.4732	18.7100	0.8805	0.8120
5	0.4234	0.0801	14.4800	0.9419	0.8119
6	0.1753	0.4240	62.1500	0.8286	0.7735
7	0.4652	0.0261	46.9000	0.4425	0.5617
8	0.4893	0.4647	30.4800	0.8639	0.8898

5. Experiments on Tomato Recognition and Optimization Based on SVM

5.1. SVM and Kernel Functions

SVM can convert pattern recognition problems into quadratic programming optimizing problems based on structural risk minimization method and kernel functions [22]. Structural risk minimization principle has advantages on solving small sample, nonlinear, high dimension and local minimum problems. The diversity of kernel functions greatly increases the application fields of SVM through finding suitable kernel functions for different problems. Therefore, the nonlinear separable problem can be solved through mapping nonlinear separable feature vector space to linear separable feature vector space by using the kernel function, and then classified by linearly separable SVM.

The optimal classification function obtained by quadratic programming method is:

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{n}\alpha^* y_i K(x_i, x) + b) \tag{14}$$

Where α^* is the Lagrange multiplier, b is a classification threshold, K (*) is the kernel function.

To get SVM, kernel functions are applied to map the nonlinear problem to a linear problem and solve the optimal class surface in the transform space. Common kernel functions are:

1) Linear kernel function: $K(x, x_i)= x \cdot x_i$;

2) The Radial Basis Function (RBF) kernel Function: $K(x, x_i) = \exp\left[-\|x - x_i\|^2 / 2\sigma^2\right]$;

3) Polynomial kernel function : $K(x, x_i) = (x \cdot x_i + 1) \cdot d$, d is a positive integer;

4) Sigmoid kernel function: $K(x, x_i) = \tanh[\alpha(x, x_i) + q]$

5.2. Recognition Experiments and Analysis

Recognition accuracy is an important index to measure model recognition effects, the paper defines the recognition accuracy as:

$$\eta = \frac{i}{N} \times 100\% \tag{15}$$

Where i is the correct identification number of tomatoes, N is the sum of tomatoes in the test area.

In the experiment, the target tomato was marked as 1 and the background as 0. Thus the recognition problem was converted into a two-class classification problem. SVM based on four different kernel functions was applied to train the samples mentioned in Section 3.3 of this paper and build classification models. Classification recognition results for training samples and testing samples are shown in Table 2. In Table 2, σ^2 is set 2 in the radial basis kernel function, and d is set 3 in the polynomial kernel function, α and q was set 3 and -1 respectively in the Sigmoid kernel function. From Table 2, we can see that the recognition time of linear kernel function is the shortest, which is 257 ms, while the Sigmoid kernel function takes a longer time in the recognition, is 348 ms. In addition, the recognition accuracy of the radial basis kernel function and polynomial kernel function is 95.7% and 92.7% respectively, significantly higher than that of the linear kernel function and Sigmoid kernel function.

Table 2. Tomato Image Recognition Accuracy with Different Kernel Functions

kernel function	The number of support vectors	Training accuracy/%	Testing accuracy/%	Running time/ms
Linear	36	65.8	63.4	257
Polynomial	114	92.7	90.6	286
RBF	154	95.7	94.8	265
Sigmoid	682	59.5	50.3	348

Due to the identification accuracy is more important than other recognition performance indexes, in order to further verify the recognition accuracy and stability of SVM, we changed the parameter values of the polynomial kernel function and radial basis kernel function during testing. The recognition accuracy results are shown in Table 3.

Table 3. Comparison on Recognition Accuracy between Polynomial and Radial Basis Kernel Function

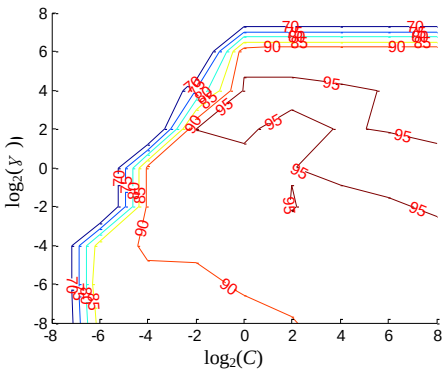
Polynomial kernel Function					Radial basis kernel function				
d	*C*	*SV*	Training accuracy	Testing accuracy	*γ*	*C*	*SV*	Training accuracy	Testing accuracy
1	0.25	244	80.56	65.25	0.25	0.25	124	93.67	91.61
	1	269	79.11	66.73		1	89	94.22	92.81
	64	146	89.79	83.65		64	73	95.17	91.33
2	0.25	254	90.34	88.38	4	0.25	67	94.44	92.12
	1	248	93.33	85.52		1	64	94.94	92.71
	64	187	93.61	88.87		64	58	95.36	94.96
3	120	138	92.23	89.24	16	120	145	94.76	92.73
	500	13011	93.38	89.11		500	108	95.24	93.88
	1600	7	93.24	88.32		1600	93	95.30	92.54

Notes: *d* is the Polynomial order; *C* is penalty parameter; *SV* is the number of support vectors; *γ* is the model parameters.

In Table 3, *d* is the order of the polynomial kernel function. $\gamma$is the model parameters of the radial basis kernel function and set as $1/2\sigma^2$. *C* is penalty parameters. Comparing Table 2, and Table 3, it shows that the maximum recognition accuracy of training and testing samples is 93.61% and 89.24%, and the minimum value of training and testing samples is 79.11% and 65.25% respectively through changing the order of polynomial kernel function and penalty parameters, which has large variation range in recognition accuracy. While the internal parameters and penalty parameters of the radial basis kernel function are changed, the maximum recognition accuracies of training and testing sample are 95.36% and 94.96%, and the minimum values training and testing samples are 93.67% and 91.33%. Therefore, the stability of recognition accuracy of SVM with radial basis kernel function is better than that of SVM with polynomial kernel function. Moreover, the maximum recognition accuracy of radial basis kernel function is 1.75% higher than that of polynomial kernel function. Therefore, SVM with radial basis kernel function is super in the mature tomato image recognition.

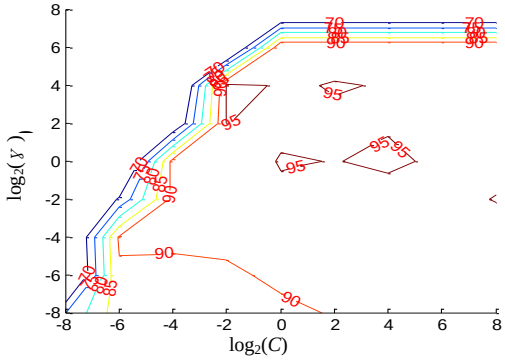
5.3. Parameter Optimization

Penalty parameter *C* and the model parameters *r* are two important parameters of RBF kernel function. To obtain the optimal parameters of SVM model, we have optimized parameters applying cross-validation and grid search method [23] to improve the recognition accuracy of classification during tomato picking. In cross validation, the parameter *C* and *r* are affected by the number of classification subsets *n*, and then affect the testing accuracy. In this paper, the training set is divided into *n* subset, in which *n*-1 subsets for training, and the rest one for testing. Each subset in training set is tested once, and the cross validation accuracy is defined by the percentage of correct classification of testing data. The cross validation can avoid over fitting problems. In the grid search, setting different *C* and *r* values, optimal parameter values are obtained when the recognition accuracy reach to the maximum. The parameter optimization results of radial basis function are shown in Figure 5.



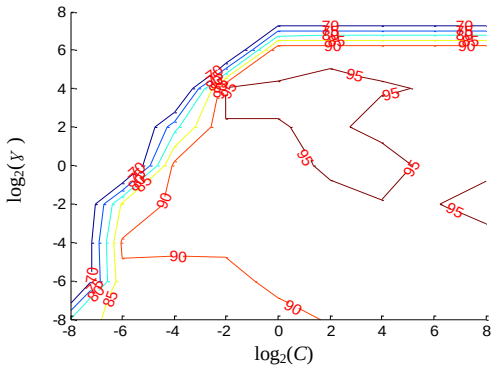
a. Contour line during parameter optimizing when *n*=2

(the maximum recognition rate is 95.6% when *C* = 1 and *γ*=16)



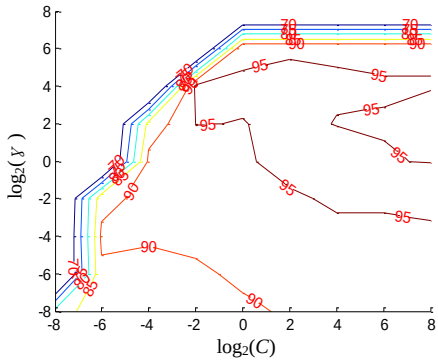
b. Contour line during parameter optimizing when *n*=5

(the maximum recognition rate is 96.6% when *C* = 4 and *γ*=16)



a. Contour line during parameter optimizing when *n*=7

(the maximum recognition rate is 96.9% when *C* = 4 and *γ*=16)



d. Contour line during parameter optimizing when *n*=10

(the maximum recognition rate is 96.8% when *C* = 1 and *γ*=16)

Figure 5. Optimal Parameters of Cross Validation and Grid Search Method with Different Subset Numbers

It is indicated from Figure 5, that the maximum recognition accuracy is 96.8% when the number of subset is 2 or 10, and the parameter *C* and *r* is 1 and 16 respectively through model parameter optimizing. While the number of the subset is 5 or 7 respectively, the parameter *C* and *r* is 4 and 16, the maximum recognition rate reaches to 96.9% with the increase of 1.2%. The experiment results also show that SVM model can be optimized to improve obviously tomato recognition accuracy by cross-validation and grid search method.

6. Conclusions

This study developed ripe red tomato fruit recognition based on light-independent images and SVM. In this method, tomato fruit images were processed according to illumination irrelevant principle, which can make tomato recognition not affected by environmental light. Classification recognition based on SVM was realized after a series of image processing, such as tomato light-independent image segmentation, multi-objective separating and the target area extracting, and then extracting the feature, *etc*. The experiment results showed the light-independent processing can eliminate the environment light intensity effect. Multi-objective tomato fruits are

separated using watershed algorithm based on distance transform, which solve the problem of fruit shading each other. The recognition accuracy of the training samples and test samples reaches 95.36% and 94.96% respectively applying the SVM with radial basis kernel function, and it also has strong stability.

Model parameters of SVM with radial basis kernel function were optimized by cross validation and the grid search method. The optimization results showed that the maximum recognition rate reaches to 96.9% when the number of training subset is 5 or 7, and the optimum parameter C and r is 4 and 16 respectively. The SVM parameters optimization can improve the recognition accuracy of tomato fruits, which provides foundation for further research on the vision system of the picking robot.

Acknowledgments

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