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LS-SVM Recognition of Fruit Using in Harvesting Robot Based on RIO-HOG Feature

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Abstract: To solve the problems occurred in the recognition of oil-tea camellia, such as the big error, lack of universality and much time consuming, the paper propose a new algorithm for fruit recognition, where Region Of Interest (RIO), Histogram of Oriented Gradients (HOG) temperature and Least Square Support Vector Machine (LS-SVM) are applied. First, the images are detected from HSV (hue, saturation, value) color information. The HOG temperature, calculated using four regions of interest (ROI), is input to an LS-SVM classifier, which detects the fruit. The performance of the model was verified by experiments. The vector sizes were effectively reduced and a higher detection speed was achieved without compromising accuracy (relative to conventional approaches).
The detection accuracy can respectively achieve 95.5%, 89.4% and 96.7% for isolated fruit, overlapped fruit and background, which is shown the excellent performance of the proposed algorithm.

Keywords: Image identification, Feature algorithm, Least squares support vector machines, Harvesting Robot

1 Introduction

Recognition of fruit (including the identification and location of the fruit) is extremely critical in vision system of fruit picking robot, the ability to quickly and accurately identity the fruit directly affect the timeliness and reliability of the robot [1]. Stajnko [2] and Jimene [3] obtain and process image of fruit trees with thermal imaging camera and laser imaging apparatus, etc. Van Henten [4] achieved to identify and locate the fruit using binocular 3D vision system. Yin Jianjun [5], Cai Jianrong [6], Bulanon [7] proposed different solutions and made some progress in the area of appropriate color space, fruit image segmentation, feature extraction and positioning.

Although the above references achieved some progress in effect of fruit identification, they focused on analysis and processing of isolated single fruit, they do have certain limitations in recognition of the overlap fruit, for example, the useful information in fruit image is only limited to graysacle, texture, shape and other information. Due to the similarity of the fruit, it is difficult to separate the overlapping fruit with the existing information (including Grayscale, texture, shape), it is necessary to design relevant algorithm to find the boundary and reconstruction fruit shape, however, these algorithms are highly specified, lacking universality. In the existing literature, most research focused on the simple case of unobstructed fruit image separation, less study on the complex cases like clustering and overlapping fruits.

Xie Zhiyong [8] did some research on clustering and overlapping strawberries identification with Hough transform, however, it has some limitation in recognizing speed and accuracy. Yin Jianjun etc. [9] proposed a watershed transform algorithm to search for boundaries of clustering or overlapping tomatoes and automatically separate the ripe tomato in the image where different growth state of tomatoes cluster in the field. However, the watershed transform algorithm may fail due to non-structural environment, the reliability of the algorithm is low. Cai Jianrong etc. [10] calculated center and radius of fitting circle for citrus with Hough transform, since the Hough transform has to vote for all the possible cases, the efficiency of the algorithm is obviously low.

In the existing feature extraction methods, Histogram of Oriented Gradients (HOG) based Region of Interest showed excellent detection performance, the method of extracting utilizes less dimension of the feature vector,

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which make the calculation of feature extraction and the computational classifier training and classification less, greatly enhance the system running speed. Regarding to piking robot's low accuracy in identifying clustering fruit and long processing time, this article designed identification method for slightly overlapping oil-tea camellia with characteristics of ROI based HOG as input of LS-SVM(Support Vector Machine) is the latest content in statistical learning theory, regarding to classification and regression problems, Vapnik proposed a Universal Learning Algorithm for Machine learning laws under a small quantity of samples [11]. SVM utilize structural risk minimization (SRM) principles to improve the generalization ability, which provide a better solution to small sample, nonlinearity, high dimension and local minima problems and widely used in pattern recognition, signal processing and timing sequence estimating areas [12]. LS-SVM is an extension of SVM, optimizing parameters uses the squared term, replaces the inequality constraints in SVM with equality constraints [13], transforms the Quadratic programming problems into linear equations which can be solved by Least Squares Method, which greatly reduce the complexity of calculation and improve the speed of calculation [14].

2 Algorithm

The algorithm put forward in this article can recognize the isolated and overlapping fruits therefore the process of recognition can be divided into following steps: first of all, transforming the pictures taken by the camera into HSV color space, setting and withdrawing the RIO area of the fruits and calculating the HOG characteristics in the RIO area and inputting them into the pattern recognizer LS-SVM so that to finish the recognition of the overlapping fruits as shown in the picture 1 in which the pictures are shot under the condition of natural light and the pictures treatment and the LS-SVM pattern recognition shall be finished in the software Open Computer Vision Library (OpenCV) and Matlab9.0a.

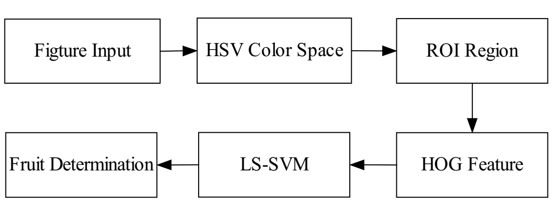


Fig. 1: Algorithm flow chart.

2.1 HSV color space transformation

Because it shall have relatively high robustness to ensure the color changes such as brightness and contrast ratio, it shall not be performed in the RGB color space. The HSV space is the non-linear transformation for the RGB space and it transforms the R, G, B values that have strong relativity originally to H, S, V values that the relativity becomes weak in which H and S are identical to the way people feel colors. Each uniform color area in the HSV space shall correspond a relatively identical Hue to make the Hue cut the color area alone. HSV change is easy to calculate and reversible, in the mean time HSV space also enables to satisfy the properties such as uniformity, compactness, integrality as well as natural gender. This essay transforms the pictures color space to HSV with the software Open Computer Vision.

Normalizing R, G, B, R, G, $B \in [0, 1]$, and then normalize Hue transformed, then H, S, $V \in [0, 1]$, the transformation formula from RGB to HSV is:

$$V = \max(R, G, B) \tag{1}$$

$$Delta = V - \min(R, G, B) \tag{2}$$

$$S = \begin{cases} 0, & if\ V = 0 \\ \dfrac{V - \min(R, G, B)}{V}, & else \end{cases} \tag{3}$$

Let

$$r = \frac{V - R}{Delta}, \quad g = \frac{V - G}{Delta}, \quad b = \frac{V - B}{Delta} \tag{4}$$

$$6H = \begin{cases} NaN(undefined) & if\ S = 0\ that\ is\ V = 0 \\ 1 - g & if\ V = R, \min(R, G, B) = B \\ 5 + b & if\ V = R, \min(R, G, B) = G \\ 3 - b & if\ V = G, \min(R, G, B) = R \\ 1 + r & if\ V = G, \min(R, G, B) = B \\ 5 - r & if\ V = B, \min(R, G, B) = G \\ 3 + g & if\ V = B, \min(R, G, B) = R \end{cases} \tag{5}$$

When Hue transforms from 0 to 0.1, corresponding color transforms from red to yellow, green, blue-green, blue, purplish red and then back to red, in fact both 0 and 0.1 represent the value of red. When the saturation changes from 0 to 1.0, corresponding color or Hue changes from unsaturation (gray shade) to full saturation (no white component). Brightness changes from 0 to 1.0, corresponding color will become brighter and brighter. Therefore the value is 0 on the top of the circular cone, all colors become black, saturation is 0, and H value has no meaning at this time.

2.2 Setting up ROI area

The traditional method is to calculate the HOG about the whole color space, when the size of Cell is 8×8 and the size of Block is 16×16, Block step-by-step is 8 pixels and gradient direction is 9 sections, then the feature vector obtained from the whole color space sized $64 \times$

128 is 3780 dimensions, it is clear that whether in extraction of the feature vector or in training and classification of categorizer, it will lead to problems such as big error and long-term calculation. However it is found through analysis that features of isolated and overlapping fruits mainly show fruits all around and HOG of central area of the fruit has almost no function about the classification. In addition, HOG in the background of the sample is not only has no function on classification but the interference will arise. Therefore we can consider that only to choose some important areas in the color space as the interested area to calculate its HOG so that to reach the purpose of increasing the resolution ratio and decreasing the calculation time. The essay sets 5 ROI areas (RIO1, RIO2, RIO3, RIO4) according to the outline of oil tea fruit and these areas basically have covered the outline of oil tea fruit as it is shown in picture 2.

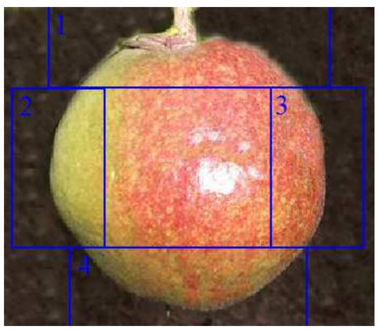


Fig. 2: Oil-tea camellia ROI zoning map.

2.3 Drawing HOG characteristics

HOG characteristic mainly describes gradient distribution characteristic in part to perform the target test to obtain better performance [15]. HOG characteristics show gradient distribution characteristics in part of area through extracting the gradient distribution in part area. HOG describes the sub procedure of extraction in 3 steps as it is shown in picture 3. The size of the image in picture 3 is selected 40 $\times$ 50 pixels and the size of cell is 5 $\times$ 5 pixels, 2 $\times$ 2 group of cells is composed of one Block, Bin=9, therefore the final HOG feature vector dimension is $2268 = 9$ bins $\times$ (2×2) cell $\times$ (7×9) blocks.

(1) Calculating the gradient magnitude and the direction.

$$m(x,y) = \sqrt{G_x^2 + G_y^2} \tag{6}$$

$$\theta(x,y) = \arctan(\frac{G_y}{G_x}) \tag{7}$$

The formula (6)and (7) calculate the gradient magnitude and the direction respectively, in which *Gx* and *Gy* represent the gradient in horizontal and vertical direction. The direction of gradient θ (x, y) can be set as $0-\pi$ or $0-2\pi$. The direction of gradient shows the direction of gray variation around the pixel point, the range of gradient m (x, y) shows the size of gray variation.

(2) Setting up the cell histogram, the image shall be divided evenly into $a \times b$ interfacing reseaux according to the space location and each reseau is called the cell, it shall be counted the gradient direction histogram according to pre-set direction in cell, it shall vote with gradient magnitude or its square or square root.

(3) Describing the character block. To explain the changes of brightness or contrast ratio, the gradient magnitude must be normalized in part, forming a large block with interfacing cell (2×2), and interfacing blocks interlaps meaning each cell has the contribution about the final feature descriptor of character more than once. HOG feature descriptor is a vector that is composed of all formalized cell histogram in the block.

(4) Block gradient formalization. Due to influence such as illumination, the transformation range of gradient is relatively large, it is difficult for categorizer to adapt to its transformation, first of all calculate the density of histograms in each block after obtaining HOG feature vector mentioned above in order to increase precision and then perform the formalization of respective small units in block according to the density value.

Standardization of LI-Norm and L2-Norm:

$$v^* = \sqrt{\frac{v}{\|v\|_k + \varepsilon}} \tag{8}$$

Where, v is the feature vector prior to standardization and v^* is the feature vector after standardization, $\|v\|_k$ represents k-norm, e is a constant to prevent that the divisor is 0.

Standardization of L1-Hys and L2-Hys: after standardization of L1-Norm and L2-Norm, the maximal value shall be limited to threshold value (for instance 0.2) and standardize L1-Norm and L2-Norm again.

2.4 Recognition principle of smallest SVM in two times

Relative to standard SVM, the smallest SVM in two times is a kind of extension put forward by Suykens [16], it replaces inequality constraint with equality constraint. Set n samples and corresponding categories shall be $y_1, y_2, \ldots, y_n$, in which the dimension of input space are $x_i \in R^d, y_i \in \{1, -1\}$, $i = 1, \ldots, n$, d is the dimension of input space. Its constraint condition of the formula is:

$$\min_{\omega,b,\xi} J_{LS}(\omega,\xi) = \frac{\|\omega\|^2}{2} + \frac{\gamma}{2}\sum_{i=1}^{n}\xi_i \tag{9}$$

$$\text{s.t } y_i[\phi(x_i) \times \omega^T + b] = 1 - \xi_i, i = 1, 2, \cdots n \tag{10}$$

Where, $\xi_i \geq 0$ is the relaxation factor and $\gamma > 0$ is the penalty function.

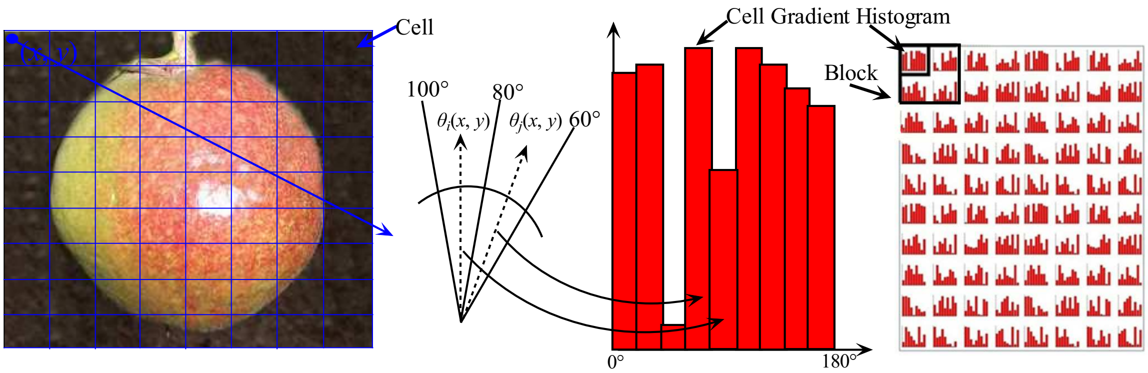


Fig. 3: HOG feature detection process sketch maps.

LS-SVM optimization finally can be transformed to solve the linear equation with Lagrangian multiplier method:

$$\begin{bmatrix} 0 & y_1 & \cdots & y_n \\ y_1 & y_1y_1K(x_1,x_1)+\frac{1}{\gamma} & \cdots & y_1y_nK(x_1,x_n) \\ \vdots & \vdots & \vdots & \vdots \\ y_n & y_ny_1K(x_n,x_1) & \cdots & y_ny_nK(x_n,x_n)+\frac{1}{\gamma} \end{bmatrix} \cdot \begin{bmatrix} b \\ a \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tag{11}$$

In solving the linear equation we can get a_i, $i = 1,\dots,n$ and b, classification hyperplane is:

$$\sum a_i y_i K(x,x_i) + b = 0 \tag{12}$$

Finally we get the decision function which is shown as picture 4:

$$f(x) = \begin{cases} \sum a_i y_i K(x,x_i) + b > 0 y_1 = 1 & \text{Oil-teaCamellia} \\ \sum a_i y_i K(x,x_i) + b < 0 y_1 = -1 & \text{Environmental} \\ & \text{Background} \end{cases} \tag{13}$$

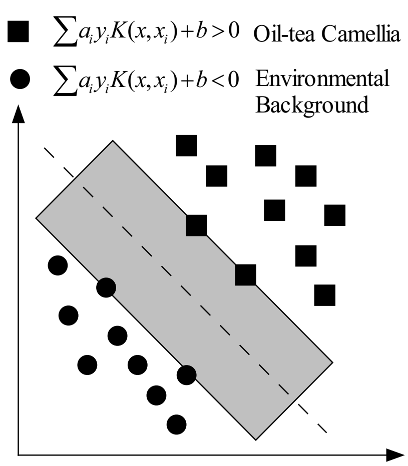


Fig. 4: LS-SVM identify principle sketch map.

3 Test result and analysis

3.1 Algorithm operational factor optimization

3.1.1 HOG characteristic parameter optimization

Dalal and Triggsz [17] have verified HOG characteristic parameter including BIN, Cell, image size, image type as well as standard type, which will have huge influence on identification accuracy. This essay will optimize HOG characteristic parameter through changing single character and remaining it, ways of change for each character parameter are shown in Tabel 1.

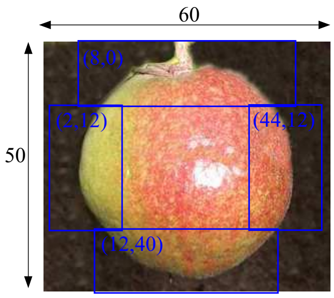
Table 1: HOG characteristic parameter change mode

Bin	Cell	Block	Image Size	Image Type	Normalization
3	3×3	1×1	90×80	Gray	L1-Norm
4	4×4	2×2	80×70	HSV	L2-Norm
5	5×5	3×3	70×60	RGBmax	L1-Hys
6	6×6	4×4	60×50	RGB-average	L2-Hys

To obtain the optimized image type, first of all we can set other parameters respectively: Bin $=6$, Cell $=6\times6$, Block $=2\times2$, image size $=80\times90$, standardization $=$ L1 $-$ Norm, in the parameter setting of the above HOG character parameters, the resolution ratio of HSV image is higher. In like manner, other HOG character parameters are optimized in order and they are: Bin $=6$, Cell $=4\times4$, Block $=2\times2$, image size $=60\times50$, image type $=$ HSV, standardization $=$ L1 $-$ Norm. According to the optimized HOG image size parameter and based on Cell and Block are integers in RIO area, then corresponding RIO area size and HOG vector dimension are shown in picture 5.

3.1.2 Learning samples quantity optimization

With the increase of quantity of learning samples, identification accuracy will increase accordingly but at



RIO	尺寸 (pixel)	HOG Dimension
1	44×12	240
2	14×28	288
3	14×28	288
4	40×10	192

Fig. 5: RIO area size and HOG vector dimension.

the same time it will promote algorithm operation time, therefore we need to find out proper learning samples quantity. To evaluate the influences of sample quantity on fruit identification accuracy, the test loads 10000 images and they are shown in picture 6. We can see from the picture that when the quantity of learning samples reaches 4000, the identification accuracy on RIO1, RIO2, RIO3, RIO4, RIO5 reaches 90% and can meet the requirements of test, therefore the remaining 6000 will be served as the final test samples.

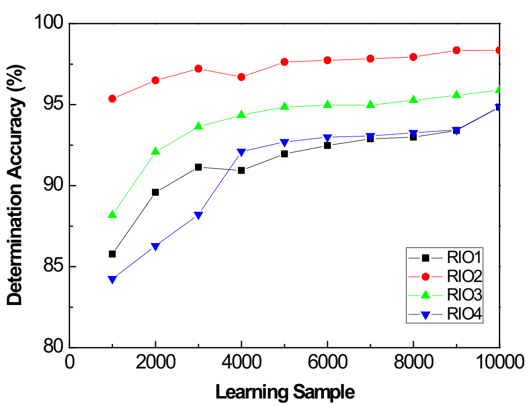


Fig. 6: Amount of learning samples impacting on the identification accuracy.

3.1.3 LS-SVM parameter optimization

In building the identification models, selection of pre-set parameter penalty factor c and nuclear parameter g will have direct influence on precision of identification models. Adaptive genetic algorithm [18] has the advantage of optimization of the subject without the analyticity of object function, therefore we can choose the best of the two preset parameters with the adaptive genetic algorithm.

The key of the adaptive genetic algorithm lies in determining fitness function and the selection of fitness function is as follows:

$$F(c,r) = \frac{1}{\sum_{i=1}^{n} (y_i - f(x_i))^2 + e} \tag{14}$$

Where, y_i is the desired output and $f(x_i)$ is the actual output; e is the small real number and its function is to prevent the denominator is zero, here is 10^{-3}. Selection of crossover probability P_e and mutation probability P_m in the adaptive genetic algorithm is the key to influence the action and performance of the adaptive genetic algorithm. This essay adopts P_e and P_m to improve the adaptive genetic algorithm with the automatic transformation of the fitness function. The adjustment method of P_e and P_m is as follows:

$$P_c = \begin{cases} 0.9 \times \sqrt{1 - \left(\dfrac{t}{t_{\max}}\right)^2} & P_c < 0.6 \\ 0.6 & \text{others} \end{cases} \tag{15}$$

$$P_m = \begin{cases} 0.1 \times e^{(-\lambda \cdot t/t_{\max})} & P_m < 0.001 \\ 0.001 & \text{others} \end{cases} \tag{16}$$

Where, t is the genetic algebra; $t_{\max}$ is the termination algebra, λ is the constant and we select 10 here.

The specific steps of optimizing LS-SVM parameters in the essay are: 1) select the learning samples and check sample, setting the section (0, 100) and (0, 10) for the penalty factor c and the kernel function parameter g, so that to produce the initial group for SVM parameter; 2) setting the crossover probability as 0.6 and the mutation probability as 0.2, the group scale 50, generation number 100; 3) training. Picture 7 is the evolutionary curve of sufficiency in finding the best parameter. We can finally get the optimal values are $c = 39.5583$, $g = 3.3263$ respectively for penalty factor c and kernel function parameter g.

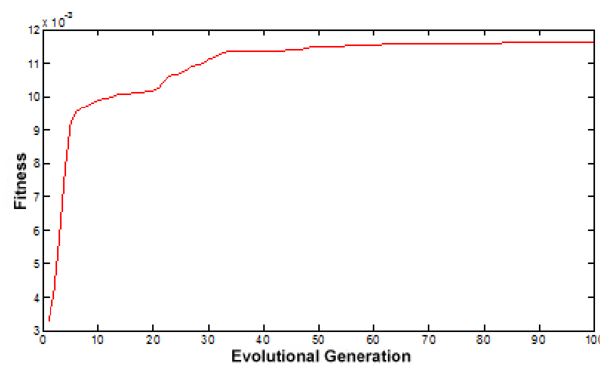


Fig. 7: Genetic algorithm to find the best parameters of fitness curve.

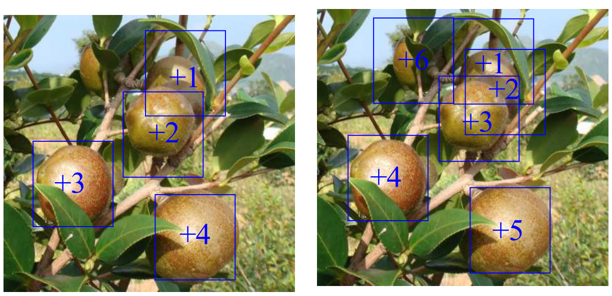
3.2 Test result

JRE for the test in the essay is PC: CPU Intel(R) 2.00GHz, Memory 4.0 GB; OS; Windows XP, Visual Studio 2010, Pencv 2.2 as well as Matlab2009a LIBSVM. To verify the superiority of algorithm fruit identification.

Table 2: The LS - SVM recognition results based on fruit RIO - HOG feature

identify image	right amount	the number of errors		sum total	accuracy
		environmental background	Fruit background		
learning samples	3982	16	2	4000	99.5%
isolated fruit test sample	1912	88	-	2000	95.6%
overlap fruit	894	106	-	1000	89.4%
environmental background samples	2901	-	99	3000	96.7%

The isolated and overlapping fruits images have been put in the learning sample and test sample in this test. The results of identification are shown in picture 8 and table 2, it can be found that the identification accuracies about the isolated and overlapping fruits as well as environment background reach 95.5%, 89.4% and 96.7%, it can be seen that the identification algorithm LS-SVM based on fruit RIO-HOG character put forward in the essay show superior identification performance.



(a) Invalid (b) Valid

Fig. 8: Fruit identification figure error and correct results.

4 Conclusion

The essay put forward a kind of LS-SVM identification algorithm based on fruit RIO-HOG characters aimed at the disadvantages such as lack of universality and long-term treatment about the traditional fruit identification algorithm in identifying overlapping fruits. The algorithm can reduce effectively the HOG vector dimension and running speed with RIO, and enhance object identification accuracy through describing gradient distribution features in part combination of HOG features and minimum SVM for two times. It is certified by the test that the algorithm is a kind of practical fruit identification method in picking fruits by the picking robot, its effects of traditional method is better and identification accuracy higher and some other features including easy in calculation, short time in operation as well as superior in identification performance.

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References

[1] Bulanon D M, Kataoka T, Ukamoto H, et al. Development of a real-time machine vision system for the apple harvesting robot. SICE Annual Conference, Sapporo, 2004.
[2] Stajnko D, Lakotaa M, Hoeevar M. Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging. Computers and Electronics in Agriculture 42, 31-42(2004).
[3] Jimenez A R, Ceres R, Pons J L. A vision system based on a laser range-finder applied to robotic fruit harvesting. Machine Vision and Applications 6, 321-329(2000).
[4] Van Henten E J, Hemming J, Van Tuijl B A J, et al. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots 3, 241-258(2002).
[5] Yin Jianjun, Mao Hanping, Wang Xinzhong, et al. Automatic segmentation method for multi-tomato images under various growth conditions. Transactions of the Chinese Society for Agricultural Machinery, , 10, 149-153(2006).
[6] Cai Jianrong, Zhou Xiaojun, Li Yuliang, et al. Recognition of mature oranges in natural scene based on machine vision. Transactions of the Chinese Society for Agricultural Machinery 1, 175-178(2008).
[7] Bulanon D M, Kataokab T, Ota Y, et al. A segmentation algorithm for the automatic recognition of Fuji apples at harvest. Biosystems Engineering 4, 405-412(2002).
[8] Xie Zhiyong, Zhang Tiezhong, Zhao Jinying. Ripened strawberry recognition based on Hough transform. Transactions of the Chinese Society for Agricultural Machinery 3, 106-109 (2007).
[9] Yin Jianjun, Mao Hanping, Wang Xinzhong, et al. Automatic segmentation method for multi-tomato images under various growth conditions[J]. Transactions of the Chinese Society for Agricultural Machinery 10, 149-153(2006).

[10] Cai Jianrong, Fan Jun, Li Yuliang, et al. Shape feature extraction of on tree citrus based on genetic algorithms [J]. Journal of Jiangsu University(Natural Science Edition) 6, 469-472(2007).
[11] Vapnik V N. An overview of statistical learning theory. IEEE Trans. On Neural Network 5, 988-999(1999).
[12] Tao S H, Chen D X, Zhao W X. Fast pruning algorithm for multi-output LS-SVM and its application in chemical pattern classification. Chemometrics and Intelligent Laboratory Systems 1, 63-69(2009).
[13] ZUO Hong-yan, LUO Zhou-quan, GUAN Jialin, WANG Yi-wei. Identification on rock and soil parameters for vibration drilling rock in the metal mine based on the fuzzy least square support vector machine[J]. Journal of Central South University 3, 1085-1090(2014).
[14] Wang Y H, Zhao X Y, Wang B T. LS-SVM and Monte Carlo methods based reliability analysis for settlement of soft clayey foundation. Journal of Rock Mechanics and Geotechnical Engineering 4, 312-317(2013).
[15] Xu Y W, Imou K, Kaizu Y, Saga K. Two-stage approach for detecting slightly overlapping strawberries using HOG descriptor. Biosystems Engineering 2, 144-153(2013).
[16] Suykens J A K, Vandewalle J. Least squares support vectormachine classifiers. Neural Processing Letters 3, 293-300(1999).
[17] Dalal N, Triggs B. Histograms of oriented gradients for human detection. Proceedings of the 2005 IEEE Computer Society conference on computer vision and pattern recognition CVPR'05, France, June, 886-893(2005).
[18] Yang Z, Gu X S, Liang X Y, Ling L C. Genetic algorithm-least squares support vector regression based predicting and optimizing model on carbon fiber composite integrated conductivity. Materials & Design 3, 1042-1049(2010).

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