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PSO OPTIMIZED SVM PARAMETERS FOR FAR INFRARED PEDESTRIAN DETECTION

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Aiming at the problem that the uncertainty of manual selection of penalty factor C and Gauss kernel parameter γ of support vector machine (SVM) in OpenCV leads to the unsatisfactory accuracy of infrared pedestrian detection, an infrared pedestrian detection method based on particle swarm optimization (PSO) optimized SVM is proposed. Samples are selected to establish the sample database. HOG feature vectors are extracted from the samples to calculate the feature matrix and put into SVM for training. Then, PSO is used to optimize the parameters of penalty factor and Gauss kernel, and SVM is trained again to get the best pedestrian classifier model, which is used to identify pedestrians. The results show that by applying PSO optimized SVM parameters to far-infrared pedestrian detection, the rate of missed detection and false detection is significantly reduced, the accuracy of pedestrian classification is significantly improved, and the operating time is shortened.

Keywords: PSO, SVM, Penalty factor, Gauss kernel parameter, Infrared pedestrian detection

1. Introduction

In recent years, pedestrian detection technology [1, 2] has matured. Compared with visible light, far infrared pedestrian detection has better research value. Far infrared pedestrian detection technology generally includes two parts: ROIs (Regions of Interest) extraction and pedestrian recognition. ROIs extraction is the selection and extraction of features. At present, the descriptions of infrared pedestrian features include Histograms of Oriented Gradients (HOG) [3], Histograms of Oriented Gradients-Intensity Self Similarity (HOG-ISS) [4], Histograms of Local Intensity Differences (HLID) [5], and Histograms of Oriented Gradients-Local Binary Patterns

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(HOG-LBP) [6], etc. Pedestrian recognition is based on the design of pedestrian classifier. The commonly used methods of pedestrian classifier are SVM [7], various boosting [8] and artificial neural network [9]. In addition, combining the optimization algorithm to search for the optimal parameters of the penalty factor and Gaussian kernel parameter, the commonly used methods are genetic algorithm [10], PSO [11], ant colony algorithm [12] and simulated annealing method [13]. The genetic algorithm has good convergence, and has the support of mathematical theory. It is suitable for solving discrete problems. The ant colony algorithm has the advantage of finding the global optimal solution, which is mainly suitable for path search, but the computational overhead is large. Simulated annealing algorithm has the advantage of strong local search ability, but the global search ability is poor, and it is mainly used in image recovery and other work. Compared with genetic algorithm, PSO has the advantages of no crossover, mutation operation, fewer parameters, easy implementation, and faster convergence to the optimal solution. Compared with ant colony algorithm and simulated annealing algorithm, PSO has low computational cost. The above advantages make it widely used in neural networks, function optimization and other fields.

Aiming at the optimal selection of SVM kernel parameters, this paper proposes a pedestrian recognition method based on the selection of HOG features and SVM to design pedestrian classifier, which combines PSO to optimize the parameters of SVM [14] to obtain pedestrian classifier. This method not only obtains the appropriate SVM kernel parameters efficiently, but also solves the problem of time-consuming optimization, and improves the accuracy of pedestrian detection, which has very important engineering significance and application value.

2. Far infrared pedestrian HOG feature extraction and SVM classifier

Far infrared pedestrian detection methods mainly include probability template matching method and statistical analysis method. In this paper, the method based on statistical analysis is used for far infrared pedestrian detection. Far-infrared pedestrian recognition based on statistical analysis is divided into two parts, one is the extraction of ROIs, and the other is the training classifier. The recognition process is shown in Fig. 1.

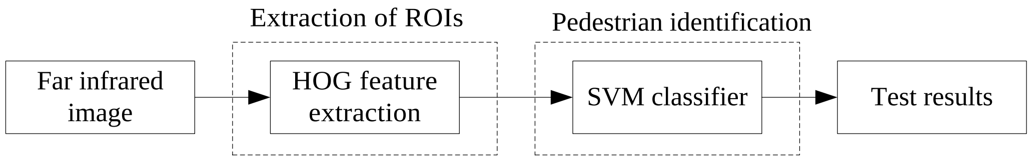

Fig. 1. Pedestrian detection system solution

2.1 HOG feature extraction

In this paper, HOG feature is extracted from candidate pedestrian area, which is a feature descriptor for detecting human targets. The core idea of HOG feature extraction is to gray the far infrared image of the target to be detected. Gamma correction method is used to normalize the color space of the input image. The size and direction of each pixel gradient are calculated. The target image area to be detected is scanned by a sliding window of 4×4 pixels to find the target. The image is divided into a plurality of connected areas (called cells) of 4×8 pixels, and the number of statistical cells constitutes a descriptor. In order to improve the accuracy, two cells form a block, and the gradient features of all cells of a block are combined to form a block descriptor. Finally, the HOG features of all blocks are combined to form a descriptor of the gray image.

In the gradient calculation phase, the first-order central gradient operator is used, and the gradient operator in the horizontal direction of the image is [1, 0, 1]. When the distribution of gradient direction is counted in each image, the cell unit is set to a circle and the number of bins in the gradient direction is set to 9. All gradients are projected into 0-180 degrees (unsigned) interval, forming a gradient direction interval every 20 degrees on average.

2.2 SVM classifier

The SVM is a two-class classification model whose basic model is defined as the linear classifier with the largest interval in the feature space. The algorithm defines one or more classification hyper planes by defining a distance function between any two points in a high-dimensional space and selects different kernel functions to determine the classification hyper plane to achieve optimal classification in high-dimensional space. The principle of SVM algorithm is as follows [15]:

The training sample set are set to be (x_i, y_i), $i = 1,2\cdots\cdots n$; $x_i \in R^d$; $d = 2$ is a two-dimensional space; $y \in (-1,+1)$ is the category mark. If the sample is linearly separable, then:

$$y_i[(w \times x_i) - b] - 1 \geq 0, i = 1,2\cdots\cdots n \tag{1}$$

Where: ω is the hyper plane normal vector and b is the hyper plane bias value.

Based on formula (1), the minimum value of $\phi(w) = \|w\|^2/2$ is found as the optimal classification surface. Thus, the optimal plane problem is transformed into a constraint as formula (2):

$$\begin{cases} \min \phi(w) = \frac{1}{2}\|w\|^2 \\ y_i[(w \times x_i) + b] - 1 \geq 0 \end{cases} \tag{2}$$

To this end, Lagrange functions can be defined as formula (3) and convert it to a dual problem:

$$l(w,b,\alpha) = \phi(w) - \sum_{i=1}^{n} \alpha_i \{y_i[(w \times x_i) + b] - 1\} \tag{3}$$

Where: α_i is a Lagrange multiplication operator.

The obtained $\phi(\omega)$ -minimum value is converted to the values of ω and b when the Lagrange function is obtained to get the minimum. The decision function of the optimal hyper plane is obtained as formula (4):

$$f(x_i) = \mathrm{sgn}((w' \times x_i) + b') = \mathrm{sgn}(\sum_{i=1}^{n} \alpha_i' y_i (x_i \times x) + b') \tag{4}$$

In order to solve the problem of sample linearity and inseparability, the relaxation variable $\varepsilon_i \geq 0$ and penalty factor C are introduced, then the constraints of the optimal classification hyper plane are as formula (5):

$$\begin{cases} \min \phi(w) = \min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \varepsilon_i \\ y_i[(w \times x_i) + b] + \varepsilon_i \geq 1 \end{cases} \tag{5}$$

Because SVM maps the input feature vector to a high-dimensional plane through a non-linear mapping to form an optimal classification hyper plane, according to Mercer theorem in the functional, formula (4) is changed to:

$$f(x_i) = \mathrm{sgn}((w' \times \varphi(x_i) + b') = \mathrm{sgn}(\sum_{i=1}^{n} \alpha_i' y_i K(x_i, x) + b') \tag{6}$$

Where $K(x_i, x)$ is a kernel function. Different kernel functions can be selected to implement different support vector machines. In this paper, the radial basis kernel function (RBF) is selected as shown in formula (7):

$$K(x_i, x) = \exp(-\gamma\|x - x_i\|^2) \tag{7}$$

Where: γ is the Gaussian kernel parameter and $\gamma \geq 0$.

Equation (6) is the optimal classification hyper plane, and the optimal hyper plane is closely related to the two factors of penalty factor and Gaussian kernel parameter. From formula (5), it can be concluded that the value of C weighs the empirical risk and the structural risk. The larger the C value, the easier it is to over-fitting. The smaller the C value, the lower the complexity of the model. Formula (7) shows that the selection of γ is closely related to the fine procedure of sample division. The smaller the value of γ, the better it can be distinguished from other samples. Therefore, it is very important to select suitable C and γ to get a good classifier.

3. Far infrared pedestrian detection

3.1 HOG+SVM far infrared pedestrian detection

After selecting the far-infrared pedestrian candidate region, the training of the far-infrared pedestrian classifier is performed. The training process of the pedestrian classifier after the HOG feature vector extraction is described as below.

(1) The OTCBVS database is downloaded. Pedestrians from Ground Truth in OSU Thermal Pedestrian Database are cut as positive samples to extract features and marked as 1. The randomly extracted unmanned samples are cut as negative samples and marked as -1 after extracting feature. The positive and negative samples are shown in Fig. 2.

(a) Positive sample (b) Negative sample

Fig. 2. Training samples

(2) The labeled sample matrix is put into SVM for training, and the kernel function is RBF. The penalty factor is C=10 and γ=8.0. The obtained classifier is reloaded to obtain the detection factor.

(3) The negative factor of the detection factor is re-trained to obtain the difficult sample, that is, negative samples with wrong classification. Then difficult samples are put into SVM to extract the feature as the negative sample marked as -1, and then retrained until the best results are obtained.

(4) The image is tested, and the best classifier is selected.

3.2 HOG+PSO+SVM Far Infrared Pedestrian Detection

From the above, it is very important to search for the best penalty factor C and Gauss kernel parameter γ. In order to optimize the parameters C and γ of the classifier, the PSO algorithm is introduced to find the best kernel parameters. The principle of PSO is as follows [16]:

A population consists of *m* particles. One of the particles p_i is iterated *k* times in a *N*-dimensional space to obtain the position, the velocity, individual extremum and global extremum as equations (8), (9), (10), (11):

$$x_k^i = (x_1^i, x_2^i, \cdots, x_n^i) \quad i = 1,2,\cdots\cdots m \tag{8}$$

$$v_k^i = (v_1^i, v_2^i, \cdots v_n^i) \quad i = 1,2,\ldots\ldots, m \tag{9}$$

$$P_k^i = (p_1^i, p_2^i, \cdots, p_n^i) \quad i = 1,2,\ldots\ldots, m \tag{10}$$

$$P_k^g = (p_1^g, p_2^g, \cdots, p_n^g) \tag{11}$$

Where: *m* is the number of particles, *k* is the number of iterations, x_k^i is the position vector of particle *i* after *k* times iteration, v_k^i is the velocity of the particle, P_k^i is the individual extremum, and P_k^g is the global extremum.

The standard PSO formula can be obtained as formula (12):

$$\begin{cases} v_{k+1}^i = w_k v_k^i + c_1\phi_1(P_k^i - x_k^i) + c_2\phi_2(P_k^g - x_k^i) \\ x_{k+1}^i = x_k^i + x_{k+1}^i \end{cases} \tag{12}$$

Where C_1 and C_2 are learning factors, which are used to adjust the individual optimal value of the particle group and the step size of the group's optimal particle direction flight. Choosing the appropriate learning factor can speed up the convergence of the algorithm and is not easy to cause local optimization. Generally, the value between 0 and 2 is selected. This paper chosen $C_1 = C_2 = 2.0$ to have the best effect; w_k is the weight (also known as the inertia factor); ϕ_1 and ϕ_2 are random numbers between 0 and 1.

The penalty factor obtained by formula (5) and the Gaussian kernel parameter obtained by formula (7) are optimized by formula (12). The optimization parameter process is shown in Fig. 3.

(1) The training samples with optimal parameters are selected. The positive samples with infrared pedestrians are marked as 1, while the negative samples without infrared pedestrians are marked as - 1. The HOG features are extracted, and the feature matrix is formed.

(2) The number of PSO is initialized to 20. The position x_i^0 and velocity v_i^0 of the PSO, the global extremum G_{best} and the individual extremum P_{best} are initialized.

(3) Cross validation is carried out. The speed of the initial particle swarm and the location of the particle swarm search are put into SvmTrain for training.

(4) The particle's adaptability is calculated. If it is better than the current individual extreme value, the particle's position is set to the P_{best}, and the individual extreme value is updated. If the optimal individual extremum of all

particles is better than the current global extremum, the optimal individual extremum is set to G_{best}, the serial number of particles is recorded, and the global extremum is updated.

(5) Whether the iteration has reached the maximum number of iterations is determined, and if it has been reached, the optimization is completed. The global optimum C and γ are returned. Otherwise, the velocity and position of the particle are updated. The program returns to step 4 to continue execution.

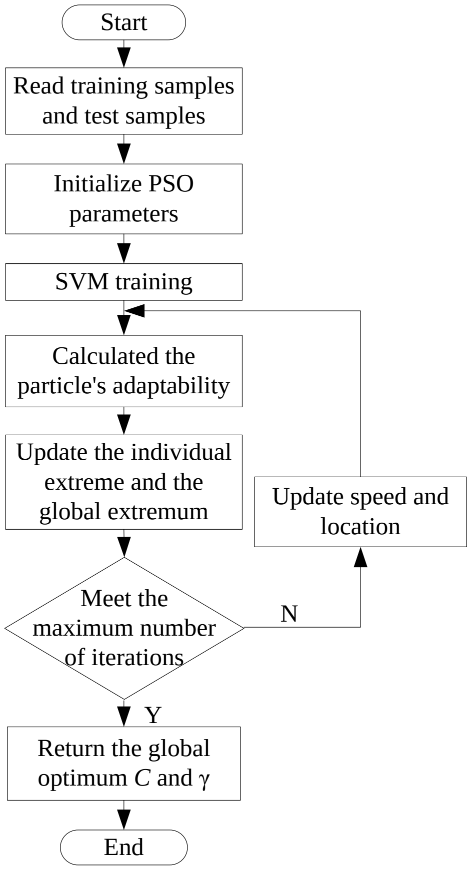

Fig. 3. The parameter optimization process of C and γ

4. Experimental results

The experimental platform of this paper is OpenCV built by VS2013. The operating environment is AMD A6-4400M APU with Radeon(tm) HD Graphics; clocked at 2.70GHz; memory is 6G; Windows 7 64-bit operating system.

Using OTCBVS far-infrared pedestrian database, each picture pixel is 360*240px, compared with visible light picture 720*480px, the picture is relatively small, and the pedestrian area is small.

Indicators describing pedestrian detection are as follows:

(1) False alarm rate *fa*: the ratio of the number of negative samples identified as positive samples to those positive and negative samples identified as positive samples;

(2) Precision *Pr*: the ratio of the number of positive samples identified as positive samples to those positive and negative samples identified as positive samples;

(3) Accuracy *Ac*: the ratio of the sum of positive samples identified as positive samples and negative samples identified as negative samples to the number of targets marked.

By selecting different feature dimensions, the accuracy data of pedestrian classification is shown in Table 1. The number 1 is the pedestrian classification accuracy obtained by HOG feature dimension 3780. The number 2 is the pedestrian classification accuracy obtained by HOG feature dimension 144 when the number of blocks of the HOG feature dimension is 8×8. The number 3 is the pedestrian classification accuracy rate obtained by HOG feature dimension 144 when the number of blocks of the HOG feature dimension is 4×4.

Table 1.

The pedestrian accuracy comparison results corresponding to the feature dimensions of different histograms

Number	bin	block	Characteristic dimension	*C*	γ	*Ac*
1	9	16×16	3780	10	8	13.34%
2	9	8×8	144	10	8	46.67%
3	9	4×4	144	10	8	40.0%

It can be seen from Table 1 that the classification accuracy corresponding to the number 2 and the number 3 after dimension reduction of the number 1 is significantly improved. For the selection of the block, the number 2 is obviously more ideal than the number 3. Therefore, the ideal simulation parameters are as follows: the number of blocks is 8×8, the feature dimension is 144, the sliding window is 16×32, and the histogram merge number is 9 for feature extraction. On the basis of determining the HOG feature dimension of 144, the OTCBVS infrared pedestrian database is used. The number of positive samples is 509, the number of negative samples is 926, and the sample of difficult sample is 11675. The SVM parameters are : classifier type is C_SVC and the kernel function is RBF.

Document 17 proposed a method for pedestrian recognition based on genetic algorithm to optimize SVM parameters in visible light. This method has the disadvantage that it does not fall into local extreme points and leads to inaccurate optimization. In order to compensate for the shortcomings of only obtaining a single extremum in GA, this paper uses PSO to optimize SVM parameters for pedestrian recognition. The number of particle swarms is 20 and the number of iterations is 25. This method can search for global extremum and local extremum well. Due to the randomness of PSO, the SVM parameters are determined by the 5-fold cross-validation method. The optimized penalty factor and Gauss kernel parameter obtained by HOG+PSO+SVM are used to test the infrared image with resolution 360*240. The experimental results are compared with those of HOG+SVM and HOG+GA+SVM. The comparison results of the accuracy and operating time for far-infrared pedestrian recognition are shown in Table 2.

Table 2.

The comparison results of the accuracy and operating time for far-infrared pedestrian recognition

Classifier type	HOG+SVM	HOG+GA+SVM	HOG+PSO+SVM
Penalty factor *C*	10	0.8	1.0
Gauss kernel parameter γ	8	0.1	0.25
Cross validation rate (%)	78.7%	79.2%	79.6%
Number of SVs	1455	373	353
Operating time (s)	0.510302s	0.123732s	0.123765s
Accuracy *Ac*	46.67%	83.8%	87.7%

As can be seen from Table 2, the parameters C=10 and γ=8 of the SVM are the default visible light parameter in OpenCV, and its effect in far infrared is not very satisfactory. The accuracy of pedestrian classification of SVM obtained by GA optimization is lower than that of SVM obtained by PSO optimization. The operating time of the two is similar, which is shortened to one third of the traditional HOG+SVM. The number of SVs is reduced, and the accuracy *Ac* is also improved.

The OSU Thermal Pedestrian Database sequence in the OTCBVS far-infrared pedestrian database was selected to verify its pedestrian recognition accuracy. The accuracy of far-infrared pedestrian recognition is compared by using five sequences with the number of 90, 95, 100, 105 and 110, respectively. The results are shown in Fig. 4.

The comparison results show that the pedestrian classifier obtained by PSO optimized SVM can improve the accuracy of pedestrian recognition in far infrared pedestrian detection.

The OSU Thermal Pedestrian Database sequence in the OTCBVS far-infrared pedestrian database was selected for detection. HOG+PSO+SVM pedestrian detection is defined as method 1, HOG+SVM is defined as method 2, and document 17 method HOG+GA+SVM is defined as method 3.

The number of test mark targets is 106, 98, 112, 101, 91 and 92 test sequences respectively. The results are shown in Table 3.

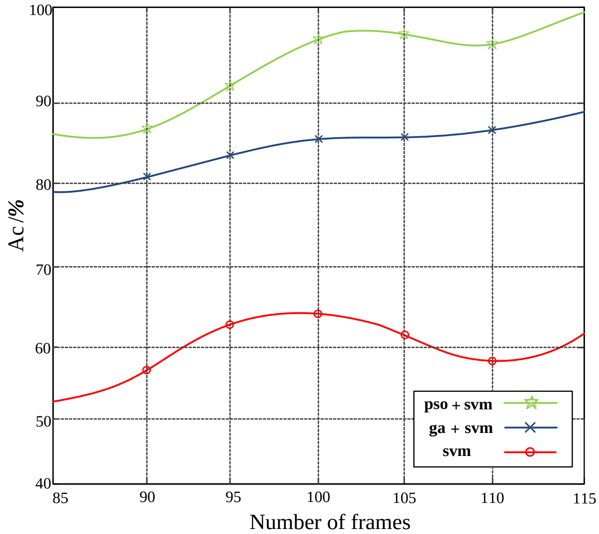

Fig. 4. The accuracy comparison result

Table 3.

Sequences detection results of OSU Thermal Pedestrian Database

Numbering	method	Number of targets marked	positive samples identified as positive samples	negative samples identified as positive samples	*fa*	*Pr*
1	method 1	106	99	2	2.0%	98.0%
	method 2	106	58	41	41.4%	58.6%
	method 3	106	85	14	14.2%	85.8%
2	method 1	98	83	2	2.4%	97.6%
	method 2	98	53	44	45.4%	54.6%
	method 3	98	78	15	16.2%	83.8%
3	method 1	112	105	3	2.8%	97.2%
	method 2	112	65	43	39.9%	60.1%
	method 3	112	95	13	12.1%	87.9%
4	method 1	101	98	1	1.1%	98.9%
	method 2	101	55	36	39.6%	60.4%
	method 3	101	85	14	14.2%	85.8%
5	method 1	91	78	2	14.3%	98.7%
	method 2	91	42	43	50.6%	49.4%
	method 3	91	72	16	18.2%	81.8%
6	method 1	92	82	3	3.5%	96.5%
	method 2	92	37	53	58.9%	41.1%
	method 3	92	72	16	18.2%	81.8%

From Table 3, it can be seen that after the parameters are optimized by method 1 and method 3, the precision of far infrared pedestrian recognition is significantly improved, and the false alarm rate *fa* is greatly reduced compared with method 2. However, compared with Method 1, Method 3 has a slightly lower precision of pedestrian recognition. From Table 3, it can be seen that the pedestrian detector optimized by PSO achieves over 85% accuracy in far infrared pedestrian detection, which proves that the precision of far infrared pedestrian detection can be improved by optimizing the parameters of SVM. Through the previous experiments, the key codes of HOG feature parameters and SVM parameters are as follows:

HOGDescriptor hog(Size(16, 32), Size(8, 8), Size(8,8), Size(4,8), 9);

CvSVMParams param(CvSVM::C_SVC, CvSVM::RBF, 10, 0.25, 1.0, 1.0, 0.5, 1.0, NULL, criteria); The pedestrian classifiers obtained by HOG+SVM and HOG+PSO+SVM are used for far-infrared pedestrian recognition, as shown in Fig. 5.

(a) HOG+SVM (b) HOG+PSO+SVM (c) HOG+SVM (d) HOG+PSO+SVM

Fig. 5. Pedestrian test results comparison chart

It can be seen from Fig. 5 that the far-infrared pedestrian recognition precision obtained after optimizing the parameters is effective. This method has a good effect in far infrared pedestrian recognition. The ideal parameters obtained are put into the SVM for training to obtain a pedestrian classifier.

5. Conclusions

Aiming at the accuracy and operating time of far-infrared pedestrian detection, an infrared pedestrian detection method based on PSO optimized SVM is proposed to find the ideal parameters under the conditions. Compared with the pedestrian classifier obtained by the traditional HOG+SVM training, the pedestrian classifier obtained by HOG+PSO+SVM not only improves the far infrared pedestrian precision and the system running speed, but also reduces the false detection rate and increases the accuracy of pedestrian recognition. The experimental results show that the method has achieved good results in far infrared pedestrian recognition.

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