Vehicle-mounted Infrared Pedestrian Detection based on NLDWPSO-SVM

Yuanbin Wang, Huaying Wu, Yujing Wang and Jian Zhang

Abstract—**Vehicle-mounted infrared pedestrian detection is significant to automotive driver assistance system. Aiming at the inefficiency of support vector machine (SVM) in infrared pedestrian detection, the modified particle swarm optimization (PSO) algorithm is utilized to optimize the parameters of SVM for the improvement of detection rate. Firstly, the gradient histogram features and the brightness histogram features of the training samples are extracted, respectively. The trained SVM is used as the classifier for infrared pedestrian detection. At the same time, the penalty factor *C* and kernel function parameter σ are optimized by the modified PSO. In view of the problem from the value of inertia weight in PSO, a nonlinear decreasing inertia weight (NLDW) strategy is proposed to adjust the value of inertia weight dynamically and avoid the problem of PSO falling into local optimum and low optimization accuracy. Experiments show that the proposed method can improve classification accuracy effectively, and pedestrian detection has better generalization ability.**

Index Terms—**infrared pedestrian detection, NLDWPSO, SVM, feature extraction**

I. Introduction

Pedestrian detection is to segment and locate pedestrians from the background. It has a strong momentum of development and has brought great technical value in all fields of intelligence [1]. Generally speaking, the brightness of the pedestrian in the infrared image is higher than that of the background, and it is not easily affected by light, texture, shadow and other factors. Compared with pedestrian detection in the visible light environment, infrared pedestrian detection has significant advantages [2-3]. Vehicle-mounted infrared pedestrian detection is significant to automotive driver assistance systems [4], which can provide help to drivers and reduce traffic accidents. Therefore, infrared pedestrian detection method with strong anti-interference and high accuracy has great research significance.

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Yuanbin Wang is an Associate Professor at the College of Electrical and Control Engineering, Xi'an University of Science and Technology, Shaanxi Xi'an 710054, China. (corresponding author phone: +18209280530; e-mail: wangyb998@163.com)

Huaying Wu is a postgraduate at the College of Electrical and Control Engineering, Xi'an University of Science and Technology, Shaanxi Xi'an 710054, China. (e-mail: wuhuaying_1999@126.com).

Yujing Wang is a postgraduate at the College of Electrical and Control Engineering, Xi'an University of Science and Technology, Shaanxi Xi'an 710054, China. (e-mail: 1143467152@qq.com).

Jian Zhang is a postgraduate at the College of Electrical and Control Engineering, Xi'an University of Science and Technology, Shaanxi Xi'an 710054, China. (e-mail: 2545504791@qq.com).

Many researchers at home and abroad have made great contributions in this field [5]. Pedestrian detection methods for infrared images are mainly divided into three types. They are based on region of interest (ROI) segmentation, template matching, and statistical classification [6], respectively.

(1) **Infrared pedestrian detection method based on ROI segmentation** [3]. The candidate pedestrian region is segmented, and pedestrian detection is conducted by pattern recognition. Current infrared image segmentation algorithms are mainly divided into three types:

① Segmentation methods based on motion mainly include the background-difference method and inter-frame difference method [7]. Gan Min [8] used the background difference method to establish the background model by gaussian mixture model (GMM). The foreground of the video was separated, and the human target was recognized by support vector machine (SVM). The system was designed based on unchanged background, but both pedestrians and vehicles kept moving for the vehicle-mounted infrared pedestrian detection. Therefore, the background-difference method was not applicable. The foreground segmentation accuracy of the inter-frame difference method [7] is not high, and it is more suitable for fast-moving targets. In the vehicle-mounted infrared pedestrian detection system, the inter-frame difference method is usually only an auxiliary method.

② ROI segmentation algorithm based on image threshold. OTSU [9] can determine the threshold automatically based on the gray histogram method and the maximum inter-class variance between the target and the background. However, this method has the problems of large threshold selection errors and insufficient segmentation accuracy. Ni Weichuan [10] proposed an improved threshold segmentation algorithm for two-dimensional OTSU infrared images. By limiting the search range of threshold values, the segmentation accuracy was improved effectively. This kind of method has better performance for simple background environment, while the vehicle-mounted infrared environment is complicated, such as climate, dynamic background and many road traffic participants. Therefore, this method is not suitable for vehicle-mounted system.

③ ROI segmentation algorithm based on image features. Common image features mainly include pedestrian structure features, image gray-scale statistical characteristics, and the key point area. Literature [11] calculated the segmentation threshold of the current frame by the histogram peak, pixel gray-scale maximum, mean and standard deviation and extracted the foreground region. Then binarization, vertical edge detection, image fusion and morphological target repairing were combined to mark the connected region, and ROI that may contain pedestrian targets was separated.

Finally, effective information was made full use of and the complete foreground region was extracted. D.S. Kim et al. [12] proposed to combine image segments to generate ROI instead of intensity thresholds and took advantage of the low-frequency characteristics of far-infrared (FIR) images. Alina Miron et al. [13] first segmented the ROI for pedestrians. The histogram of oriented gradient (HOG) and intensity self-similarity (ISS) were employed to feature extraction, and SVM was used for classification. This method was highly efficient and robust, but it also had a weak real-time performance. The acquisition of ROI is a rough classification for pedestrians, which can reduce the influence from backgrounds and noise， and improve real-time performance. However, if pedestrians are missed in the process of extracting ROI, the detection accuracy cannot be guaranteed.

(2) **Infrared pedestrian detection method based on template matching.** The infrared pedestrian template is established in the infrared image. The template is matched with the detection target one by one to realize stable detection. Nanda et al. [14] captured the variations in human shape by probabilistic templates for pedestrian detection. Wang Guohua [15] proposed a new method of the infrared pedestrian probabilistic template. Based on the head adaptive positioning method, the template was fused to select the optimal template for pedestrian matching, which improved the matching overhead and accuracy. The method based on template matching needs to design enough templates to achieve excellent detection results. However, the postures of pedestrians are changeable, and the types of templates are endless, so it is difficult to construct suitable infrared pedestrian targets.

(3) **The infrared pedestrian detection methods based on statistical classification.** The positive and negative sample features of the infrared pedestrian image are extracted, and the whole image is traversed through the sliding window. Then each window is classified with a trained classifier, and the pedestrian detection results are obtained. Since there is not too much color and texture information in infrared images, infrared pedestrians are generally described with information such as brightness and edges. For pedestrian detection, Li Z. [16] proposed a mid-level feature descriptor, which distinguished pedestrians from the complex environment. The method overcome the problems caused by background subtraction and achieved better detection accuracy. In literature [17], the feature-centric efficient sliding window scheme was utilized for infrared pedestrian detection, and the randomly projected features were extracted by SVM.

Lahmyed R. [18] extracted the color-based HOG histogram and histogram of oriented optical flow (HOOF) histogram and input the features into a random forest classifier. The effectiveness of the algorithm was proved in different data sets. Li et al. [19] combined HOG features and geometric features for infrared pedestrian detection. Experimental results showed that this algorithm could improve detection performance significantly. Wang et al. [20] proposed a feature description method based on shape and multi-clue fusion algorithm to optimize the performance of infrared pedestrian tracking, which could solve the problem of occlusion and multi-infrared target tracking effectively.

In terms of classifiers, Cai et al. [21] adopted fusion saliency-based methods to detect areas containing suspected pedestrians and employed sub-images of suspected pedestrians as input to local intensity difference feature histograms. Cross-core-based SVM was adopted for final determination. This method had a higher pedestrian detection rate and a relatively short processing time. Guo et al. [22] proposed a far-infrared pedestrian detection algorithm based on the back propagation (BP) neural network, which used the image difference method to extract ROI. The Fourier descriptor of the target area was used as an input feature to train BP classifier. This method selected many different types of pedestrian samples with different shapes and had a higher recognition rate and a lower false alarm rate. However, the pedestrian posture is various, so the generalization ability is weak. Wang et al. [23] extracted the features of the brightness histogram and gradient direction histogram, and adopted an adaboost cascade classifier for sample classification, which could improve the detection rate effectively. However, it requires multiple iterations to train a strong classifier containing multiple weak ones. The training time is too long, which is not conducive to real-time operation.

Among these above target detection algorithms, the methods based on statistical classification are more effective and easier to implement than others. Therefore, this kind of method is adopted in this paper. The system is mainly divided into two steps. The first step is feature extraction, and the second step is machine learning classification. To improve the detection accuracy of vehicle-mounted infrared pedestrians, this paper mainly conducted two contributions: (1) The brightness histogram and gradient direction histogram are adopted to extract features, and the parallel feature fusion is conducted, which can extract the brightness and edge information of the image effectively. (2) NLDW-PSO algorithm is proposed to search for better SVM parameters, which can avoid falling into the local extreme value and improve the search ability of the global optimal value.

The rest of this article is organized as follows. In Section 2, we mainly describe the working principle of the proposed algorithm. The vehicle-mounted infrared feature extraction is introduced in Section 3. Then, vehicle-mounted infrared pedestrian detection based on NLDWPSO-SVM is proposed in Section 4. Next, experimental results and analysis are presented in Section 5. Eventually, the paper is summarized in Section 6.

II. WORKING PRINCIPLE

Vehicle-mounted infrared pedestrian detection mainly includes two stages: the training phase and the detection phase. In training phase, the first positive and negative training samples are input, then the HOG features and histogram of intensity (HOI) features are extracted, and parallel features are fused. Nonlinear decreasing inertia weight particle swarm optimization (NLDWPSO) is employed to optimize the parameters of SVM, and the fusion features are classified by the SVM model. In detection phase, the windows with different scales are applied to traverse the detection image in turn with the same step length, and the trained SVM model is used for pedestrian detection in each corresponding window. Finally, the windows containing

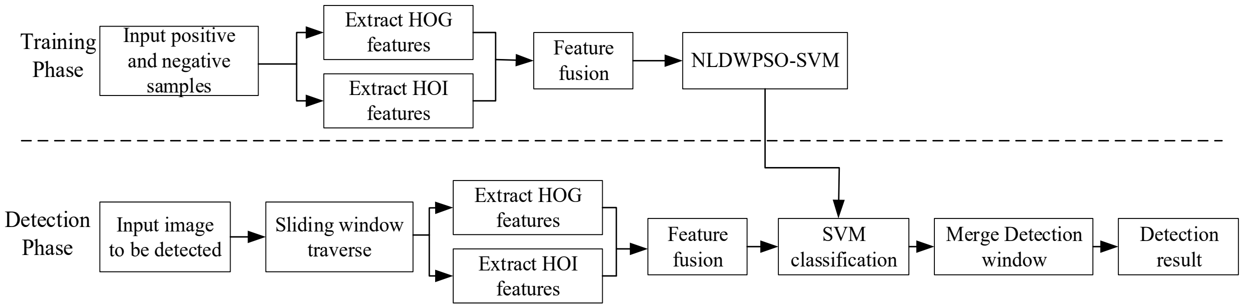


Fig. 1. Framework diagram of vehicle-mounted infrared pedestrian detection

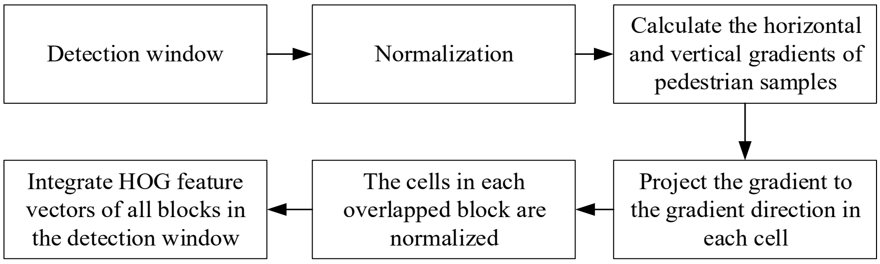


Fig. 2. HOG feature extraction steps

Fig. 3. Two pedestrian images with corresponding HOG feature images

pedestrians are fused, and the detection results are output. The detection framework is shown in Fig. 1.

III. Vehicle-mounted Infrared Feature Extraction

The classification accuracy is influenced by feature extraction greatly. In 2005, Dalal et al. first proposed the HOG feature, and they combined it with SVM for pedestrian detection and obtained high accuracy [24]. According to the research, HOG features can be used to describe the contour of pedestrians accurately and have a strong representation ability, which has particular advantages compared with other feature descriptors. In addition, the temperature of the human body is kept in a constant range, so the pedestrians in the infrared image show high brightness and are not affected by the environment easily. Based on the comprehensive analysis, HOG features and HOI features are selected and fused in this paper.

A. HOG Features

HOG is a kind of feature histogram, which is applied to extract the shape characteristics of pedestrian. Its main idea is to represent the target based on local edge gradient intensity and edge gradient direction. The HOG feature extraction steps and the HOG feature image of infrared pedestrians are shown in Fig. 2 and Fig. 3, respectively.

B. HOI Features

In infrared images, the brightness of the target object is one of the important information to distinguish the detection object from the background. The local brightness information in the image is encoded by the HOI descriptor, so this feature has stronger description ability than the simple pixel gray value or rough pixel block average value to describe the brightness information of the image. The HOI can encode its brightness information with region high-density overlap, and the difference between pedestrians and the background is described. The feature extraction steps and extraction results of HOI are shown in Fig. 4 and Fig. 5, respectively.

IV. Vehicle-mounted Infrared Pedestrian Detection based on NLDWPSO-SVM

In view of the particularity of vehicle-mounted pedestrian images, their dimension is often very high, while the number of samples is relatively small compared with the dimension. SVM has great advantages in high-dimension and small-sample classification, so it is selected as the classifier.

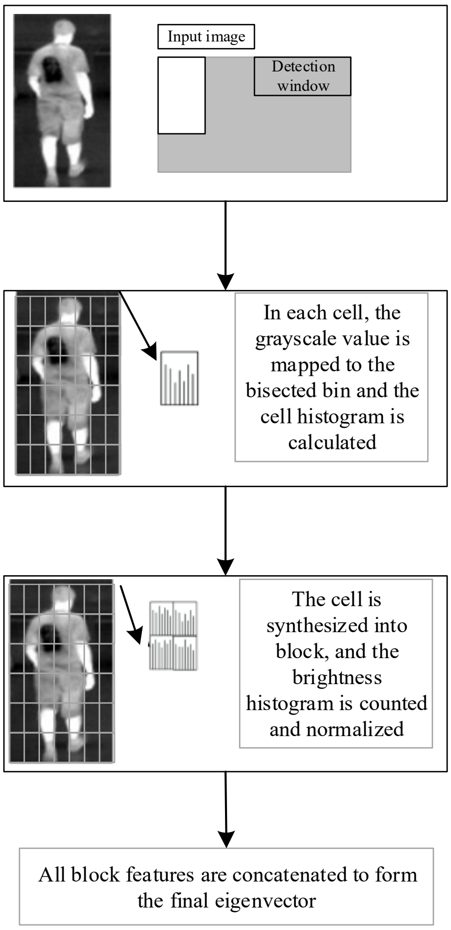


Fig. 4. HOI feature extraction steps

However, the parameter selection of SVM is not flexible enough, which affects its classification accuracy to some extent. At present, grid search and genetic algorithms are used for parameter optimization commonly. These search algorithms have different defects, such as the grid search method with long time-consuming and low precision, the genetic algorithm with slow convergence speed and complex parameters, etc. In this paper, the PSO algorithm is utilized to search penalty factor *C* and kernel function parameter σ of SVM. Aiming at the problems that PSO is easily falling into local optimization and low optimization accuracy, an improved SVM algorithm based on PSO is proposed for vehicle-mounted infrared pedestrian detection.

A. Support Vector Machine Algorithm

SVM is a binary classification model, which aims to find the optimal hyperplane and maximize the class spacing. SVM constructs the optimal classification hyperplane by mapping data from low-dimensional space to high- dimensional feature space through nonlinear mapping [25]. It can be ascribed to solve the following convex quadratic programming problem in the original space, and the constraint conditions are as follows:

$$s.t.\begin{cases} y_i(w^T\varphi(x_i)+b)\geq 1-\zeta_i, & i=1,2\cdots,m \\ \zeta_i\geq 0, & i=1,\cdots,l \end{cases} \tag{1}$$

The minimum value of the objective function is as follows:

$$\min_{w,\zeta}\frac{1}{2}\|w\|^2+C\sum_{i=1}^{m}\zeta_i \tag{2}$$

Where *C* represents the trade-off between $\|w\|^2$ and $\sum_{i=1}^{m}\zeta_i$.

$$f(x)=\mathrm{sgn}(\sum_{i=1}^{m}\alpha_i y_i k(x,x_i)+b) \tag{3}$$

Where sgn() is the symbolic function, α_i represents the Lagrange multiplier, $k(x,x_i)$ is the kernel function. The type of sample set data can be judged by the positive and negative functions.

Different SVM classifier models can be established by different kernel functions [26]. The radial basis function (RBF) has the advantages of superior classification performance and fast running speed. Therefore, the kernel function is adopted as follows:

$$\mathrm{k}(x,x_i)=\exp(-\frac{\|x-x_i\|}{2\sigma^2}) \tag{4}$$

The calculating complexity and classification accuracy of the SVM model mainly depends on the value of *C* and σ. The value of *C* impacts classification accuracy and generalization ability of the model, and the value of σ will lead to overlearning or under learning. To select the appropriate *C* and σ, the modified PSO algorithm is employed to optimize SVM model.

B. Support Vector Machine based on NLDWPSO (NLDWPSO-SVM)

Fig. 5. Two pedestrian images with corresponding HOI feature images

The principle of PSO Algorithm

PSO is an intelligent search algorithm based on population, which simulates the cooperative foraging process of birds, fishes and so on, and it is performed in the iterative recursive form [27].

The principle of PSO algorithm is described as follows. In *D*-dimensional search space, it is supposed that *n* particles $x = \{x_1, x_2, \cdots, x_n\}$ are initialized, the position of the particle *i* at time *t* is $x_i^t = (x_{i1}^t, x_{i2}^t, x_{i3}^t, \cdots, x_{iD}^t)$, and the flying velocity is $v_i^t = (v_{i1}^t, v_{i2}^t, v_{i3}^t, \cdots, v_{iD}^t)$. The individual extremum is the individual optimal position that particle *i* has experienced at time *t*, which is $P^t{}_i = (P^t{}_{i1}, P^t{}_{i2}, P^t{}_{i3}, \ldots, P^t{}_{iD})$. The global extremum is the optimal position that the whole particle swarm has experienced at time *t*, which is $P^t{}_g = (P^t{}_{g1}, P^t{}_{g2}, P^t{}_{g3}, \ldots, P^t{}_{gD})$. The velocity and position update formula of particle *i* at time *t*+1 are as follows [28]:

$$v_{id}^{t+1} = wv_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{gd}^t) \tag{5}$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \tag{6}$$

Where $1 \le d \le D, 1 \le i \le n$, *w* is inertia weight; r_1 and r_2 denote random numbers within the range of (0,1); c_1 and c_2 represent learning factors, usually set as $c_1 = c_2 = 2$.

PSO Algorithm based on NLDW

The flying velocity of the particle is the search distance, it is determined by *w*, and the searching distance is affected by *w*. Its value is employed to balance the global development ability and local search ability of particles. At present, the inertia weight linear decline strategy is widely used and expressed as follows:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t \tag{7}$$

Where *t* and $t_{\max}$ are the current iterations and the maximum iterations, respectively. $w_{\max}$ and $w_{\min}$ are the maximum and minimum value of inertia weight, respectively.

The linear decreasing strategy can balance the global search and local search ability of the algorithm effectively. But if the global optimization can not be finished in the initial period of iteration, the algorithm will fall into the local optimal search state [29].

Aiming at the problems of linear decreasing inertia weight strategy, the NLDWPSO algorithm is proposed, which can adjust the value of *w* dynamically. The specific improvement methods are as follows: the exponential function is used to control the change of *w*. With the increment of iteration times, the exponential function decreases nonlinearly. In the later stage of iteration, the sine function increases the global search ability and reduces the possibility of falling into the local optimum. The improved inertia weight can be expressed as follows.

$$w = w_{\max}(e^{-\frac{\eta t}{t_{\max}}}) + \sigma \sin(\pi \frac{t}{t_{\max}}) \tag{8}$$

Where η denotes the control factor, and it is used to narrow the range of *w* between $w_{\max}$ and $w_{\min}$. Many experiments show that $w_{\max} = 0.9$, $w_{\min} = 0.4$, when $w_{\min} = 0.4$, the value of η is calculated as 0.81. σ is the fluctuation degree of inertia weight with the value of 0.065. Fig. 6 shows the variation of *w* with iterations *t*.

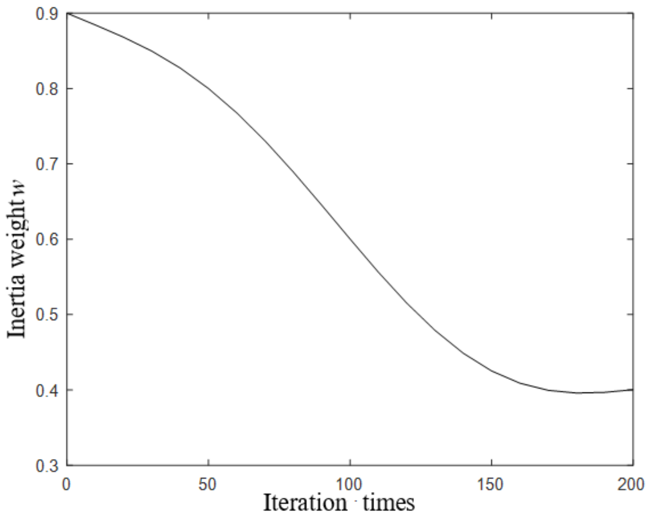


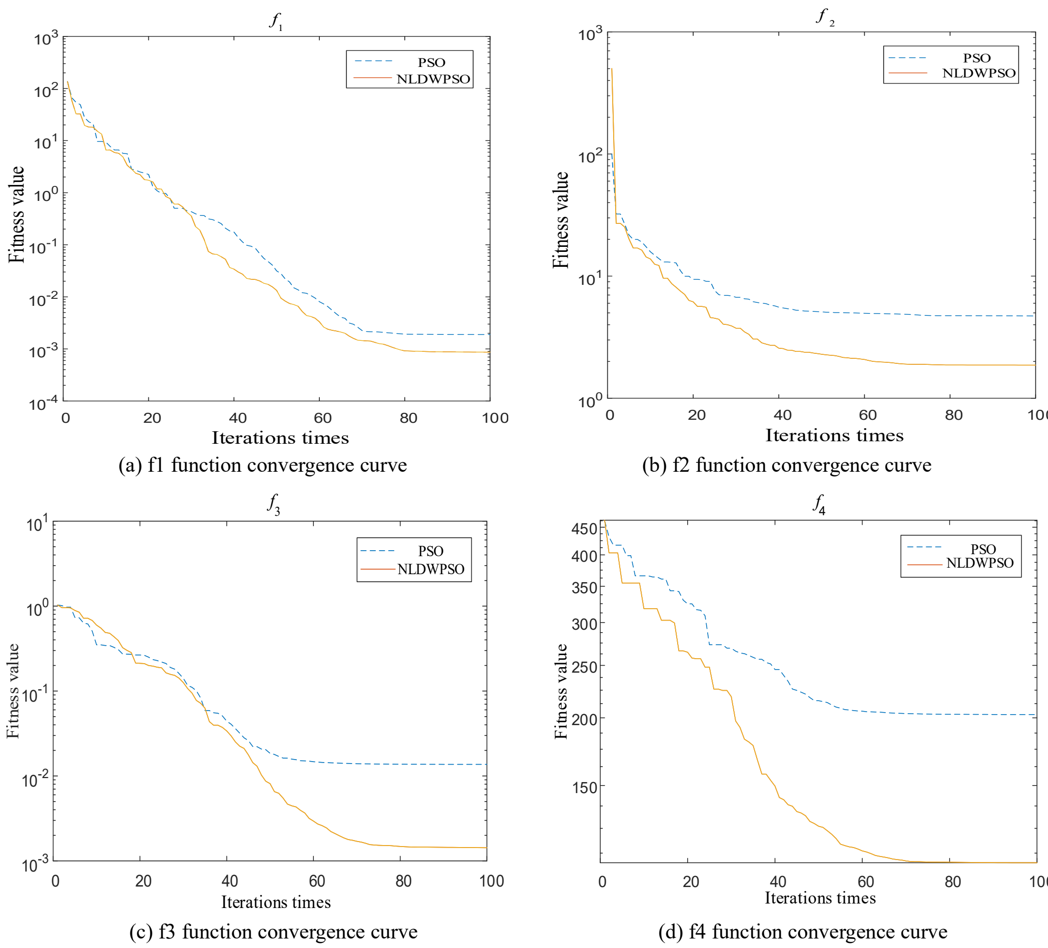
Fig. 6. The variation of nonlinear decreasing inertia weight w with iteration times t.

As can be seen from Fig. 6, *w* decreases nonlinearly with the iterations *t*. At the beginning of the iteration, the value of *w* is large and changes slowly, and the algorithm can converge to the region quickly where the optimal solution is located. In the middle part of the iteration, *w* decreases rapidly. The global search ability weakens slowly while the local search ability enhances gradually. In the later stage of iteration, *w* is almost unchanged, and the search step length is small. The fine search of particles in the local area will not miss the optimal solution. This strategy can ensure the convergence speed and avoid the algorithm from falling into the local optimum.

Performance Verification of NLDWPSO

TABLE I
FOUR TEST FUNCTIONS

Function name	Function expression	Value range
f_1	$f_1(x) = \sum_{i=1}^{n} x_i^2$	$x_i \in [-50, 50]$
f_2	$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	$x_i \in [-10, 10]$
f_3	$f_3(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	$x_i \in [-600, 600]$
f_4	$f_4(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	$x_i \in [-5, 5]$



(a) f1 function convergence curve (b) f2 function convergence curve

(c) f3 function convergence curve (d) f4 function convergence curve

Fig. 7. Convergence curves of two algorithms in four test functions

To evaluate the performance of the NLDWPSO algorithm, four test functions are utilized to test PSO and NLDWPSO algorithms. The specific formulas of the four test functions are shown in Table 1. The convergence curve of two different algorithms in four test functions is shown in Fig. 7. In order to display the curve clearly, the logarithm based on 10 is taken for the fitness value of the f_1-f_3 test function.

Fig. 7 shows the comparative curves of convergence speed and trajectory between the PSO algorithm and NLDWPSO algorithm. It can be seen that NLDWPSO algorithm has a faster convergence speed and a higher accuracy in searching for the global optimal solution than that of PSO. Therefore, the NLDWPSO algorithm can adjust the value of w dynamically and avoid falling into the local optimal search state.

SVM algorithm based on NLDWPSO

The flow chart of the NLDWPSO algorithm is shown in Fig. 8, and the specific steps are as follows:

① The particle swarm is initialized to constitute the initial particle population *X*. In addition, initial values are assigned to two parameters C and σ in the SVM model, respectively.

② Each particle is evaluated to obtain the fitness value. The classification accuracy of the pedestrians in the SVM model is selected as a fitness value, which can be expressed as follows:

$$R = \frac{n_{correct}}{n_{total}} \times 100\% \tag{9}$$

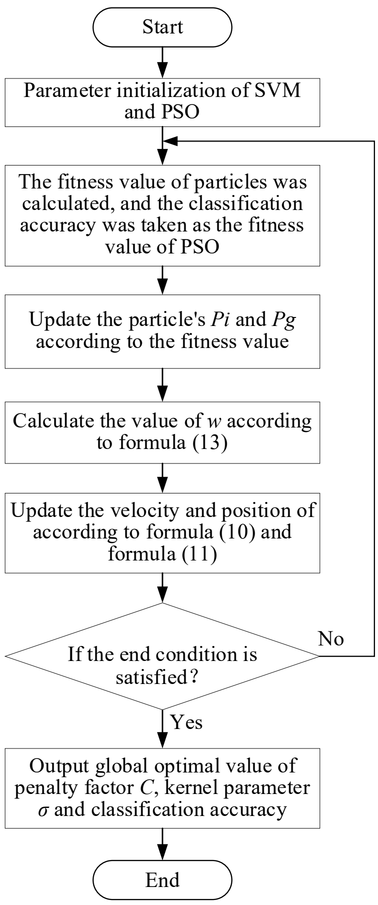


Fig. 8. The flow chart of SVM based on NLDWPSO

Where R is the classification accuracy, n_{totall} is the total number of samples, and $n_{correct}$ is the correctly classified samples.

③ Comparing the current fitness value p_c of each particle i to its individual historical optimal position p_i, p_i will be updated with the current position if p_c is better.

④ Comparing p_c of each particle i to its global best position P_g, P_g will be updated with the current position if the p_c is better.

⑤ The value of w is calculated according to formula (8).

⑥ The velocity and position of each particle are updated by the formulas (5) and (6).

⑦ If the maximum iterations are satisfied, or the optimal solution is searched out, then step ⑧ is continued, and the iteration is terminated. Otherwise, the step is turned to ② and continued.

⑧ The global optimal value of C, σ and classification accuracy are output.

C. *Multi Scale Sliding Window Detection*

In pedestrian detection, the sliding window [30] is used in selection mechanism commonly. Due to the different sizes of the pedestrians in the image, some may exceed the size of the sliding window so that the sliding window can't frame the pedestrians completely, and some may be too small, which will lead to missed detection. In this paper, the following method is adopted: Firstly, the size of the sliding window is fixed, and the image is zoomed out quickly to generate different scale subgraphs by the feature pyramid [31]. Secondly, the subgraphs with various scales are scanned by the window sliding method. In the small-scale subgraph, the sliding window will contain more information. The larger scale subgraph, the less information it contains.

V. Experimental Results and Analysis

A. *Selection of Infrared Pedestrian Image Data Set*

LSI Far Infrared Pedestrian Dataset [32] is collected by the vehicle-mounted infrared camera from the laboratory of Carlos III University, Madrid, and it can be well applied to

(a) Positive samples

(b) Negative samples

Fig. 9. Partial sample images

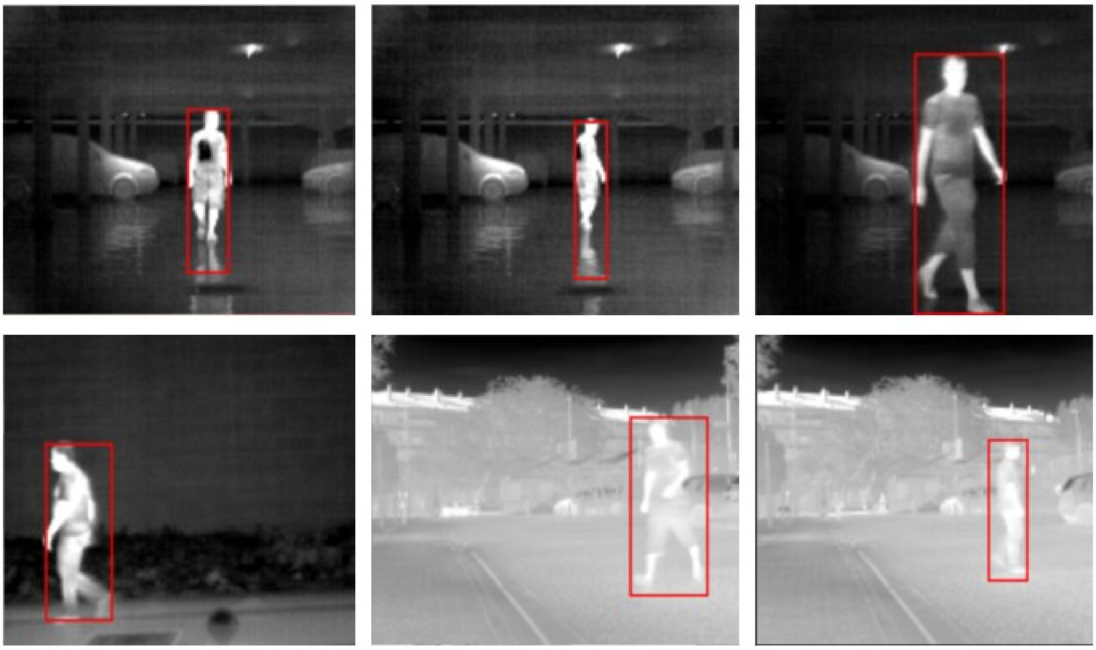


Fig. 10. Partial results of pedestrian detection

TABLE II
COMPARISON OF PEDESTRIAN DETECTION RESULTS IN TEST SET1

Test set	Methods	C	σ	Classification accuracy	Detection accuracy
Test set 1	Literature [18]	/	/	97.06%	96.39%
	Literature [19]	/	/	87.06%	85.48%
	SVM	10	0.01	87.44%	85.65%
	PSO-SVM	26.4	0.00084	93.82%	89.72%
	NLDWPSO-SVM	22.82	0.0000214	98.37%	97.95%

TABLE III
COMPARISON OF PEDESTRIAN DETECTION RESULTS IN THE TEST SET 2

Test set	Methods	C	σ	Classification accuracy	Detection accuracy
Test set 2	Literature [18]	/	/	95.36%	93.93%
	Literature [19]	/	/	90.42%	89.03%
	SVM	10	0.01	88.44%	87.73%
	PSO-SVM	26.4	0.00047	94.89%	90.43%
	NLDWPSO-SVM	22.82	0.0000016	98.37%	96.16%

automotive driver assistance systems. The data set is divided into detection data set and classification data set. There are 15,224 positive and negative samples in the detection data set, including 6,159 images in the training set and 9,065 images in the test set. There are 81592 positive and negative sample images in the classification data set, including 53598 images in the training set and 27994 images in the test set. Partial samples are shown in Fig. 9.

It can be seen from Fig.10 that the NLDWPSO-SVM algorithm can achieve accurate detection of pedestrians with different poses. Therefore, it has good stability and strong robustness.

Comparison with Different Methods

To verify the performance of the NLDWPSO-SVM algorithm, it is compared with the literature [18], literature [19], SVM with unoptimized parameters (SVM), and SVM optimized by PSO (PSO-SVM). Table II and Table III are the simulation results of pedestrian detection by selecting two groups of test sets, respectively.

As can be seen from Tables 2 and 3, the detection accuracy of the proposed algorithm is better than that of the other four algorithms, which shows that the proposed method has better classification ability. Among the two optimization algorithms of the SVM, the detection accuracy with the proposed method is higher than that of PSO-SVM. That is because the proposed approach avoids the problem of premature convergence and falling into the local extreme value, which improves the search ability of the global optimal value and has a faster convergence speed. The penalty factors and kernel parameters of SVM can be searched more flexibly, and the classification accuracy of SVM can be improved more effectively by NLDWPSO. Therefore, the detection accuracy of vehicle-mounted infrared pedestrians is improved significantly.

VI. Conclusion

In this paper, the vehicle-mounted infrared pedestrian detection method is investigated. Firstly, the HOG feature and HOI feature are used for feature extraction to obtain the edge information and brightness information of pedestrians in the infrared image. Then, SVM is used for feature classification of parallel fusion. PSO is utilized to optimize the two parameters C and σ of SVM for the improvement of its classification performance. Aiming at the defect of PSO, the strategy of nonlinear decreasing inertia weight is employed to optimize PSO. The result shows that the NLDWPSO algorithm has a stronger global searching ability and faster convergence speed. Compared with the other four algorithms, the proposed algorithm has higher classification accuracy and generalization ability, which can improve pedestrian detection accuracy effectively.

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