Forest Target Classification Research Based on Multi-class Gauss Kernel Fuzzy Support Vector Machine

Zhihui DAI, Qingqing HUANG, Wenbin LI, Chaoyi ZHANG※

***Abstract*—**For the measurement system of artificial forest environment, it was necessary to import pattern recognition method to identify and classify the different targets such as living trees and obstacles in forest environment. The features selection directly affected the classifier performance. This paper content based on independent objects' fusion point cloud data, extracted the target feature with clear distinction function, proposed a forest target classification method which based on multi-class Gauss particle size fuzzy support vector machine, the main contents were as follows: the forest environment independent objects semantic classification was unknown, the image data after segmentation and 3D laser point cloud data extraction, were used to extract the artificial forest target and obstacles color, shape, reflection strength and characteristics of three-dimension space. The import of Gauss particle size enhanced the fuzzy support vector machine which based on linear support vector machine classifier, and put forward the rise of membership function distribution based on semi convex, the decision directed acyclic graph was extended to multi-class classification. Through a large number of samples in training and learning under plantation environment, it proved that this method can effectively identify the plantation environment under the trees, fire, pedestrian these three target. Through the model parameter optimization, comprehensive average correct recognition rate can reach 96%, this result can provide accurate recognition for forest firefighter.

***Keywords*—**Laser, image, forestry target, identification, detection

I. Introduction

In order to meet the rapid forestry development, it is necessary to develop a high efficient and multi-function automatic equipment for forest tending and cutting. Due to the complex environment of forest land, poor lighting conditions, obstacles impact, these reasons will interrupt the forestry equipment operations, increase operation risk, and reduce operating efficiency. Therefore, it was required to accurately detect forest environment, identify the object and determine its position, then the operator can timely feedback safety warning, auxiliary operation of cutting, improve work efficiency, and enhance the operation capacity [1].

In the research of intelligent detection system of forestry equipment, Finland Ponce company produced harvester, it can acquire tree's accurate measurement data through laser rangefinder and angle sensor information, and improve work efficiency. The United States John Deere Company produced multiple types of harvester assembly measurement and control system. In the process of operation, through three-dimension laser scanning ranging system, tree diameter data was automatic measurement and real-time feedback. Finland Polytechnic University of Helsinki installed two 3D laser rangefinder in the logging harvester head on, used non-contact measurement method, fused inertial measurement system data, automatic acquired tree information, improved the logging harvester, section material operation efficiency and the intelligent level of [2-4]. Professor Lu Huaimin [5] used 3D laser scanning system for scanning the tree, tree DBH, higher data, so as to get the wood product, the experiment results show that laser scanning obtained wood product can replace the tradition measurement methods, in the survey of forest resources can greatly improve the working efficiency [5]. Beijing Forestry University professor Feng Zhongke [6-7] used three-dimension laser scanning system for scanning the tree, through the analysis of point cloud data, the tree height, DBH, canopy volume, surface area measurement factor were acquired, these data was compared with fallen tree after measured data, this method can satisfy the accuracy requirements in forest resource survey [6][7]. Beijing Forestry University Institute of Liu Jinhao, Ding Xiaokang [8] studied forest adoptsthe target recognition in 2D image based on laser, the laser and image were demarcated and fused, according to the characteristics of forest adoptsthe target, they taken feature extraction, used support vector machine learning algorithm, built characteristic parameters and forest adoptsthe target model, improved the recognition performance.

In the process of classification forest targets, the common used classification algorithms were AdaBoost classification algorithm [9-10], RBF neural network classification algorithm [11-12], SVM classification algorithm [13-15]. Comparison analysis among these three different machine learning algorithms, we found that AdaBoost algorithm through multiple weak classifiers were combined to obtain a strong classifier, each classifier has error limit, so there is no overfitting problem, used simple classifier, can't guarantee the final classification result, excessive human intervention limits its popularization in practical application [10]. The classification of RBF neural network had higher identifiability in target database, but its value iteration taken too much, the same density had a great influence on the initial value of output error [13]; SVM algorithm had the best classification performance, it had the best recognition output with a high accuracy rate in local database,

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while the computation time was less, it can also perform better in high dimension feature space of small samples, but the linear SVM still had some problems, the noise data existence will have a certain impact on classifier generalization ability, while aim at other multi-class target---fire, rocks, person, the SVM recognition ability was not strong, it was mainly influenced by the training process of different objectives and characteristics of the model input [14-15]. Therefore, based on the SVM algorithm, the existing multi-class recognition and generalization ability were improved, the basic parameters were optimized to further enhance the target correct recognition rate in forest area.

In the classification application of above linear support vector machine in forest environmental targets. There were two problems needing to be solved [16-17]: one was how to overcome the impact of noise, enhance the generalization ability; the second was the tradition support vector machine's duality was strong, but this paper's multi-class target was lack performance. Therefore, in this paper, we proposed a support vector machine (SVM) based on fuzzy input and fuzzy output as the basis of classifier, used Gauss particle size to describe kernel function, and put forward a new form of membership. For the duality problem to multi-class problems, this paper used a form of directed acyclic graph, and double fuzzy support vector machines were extended to multi-class problems, fuzzy support vector machine of multi-class Gauss particle size was built, this method enhanced the linear support vector machine classification ability and generalization.

II. Information Collection System Based on Laser and Image

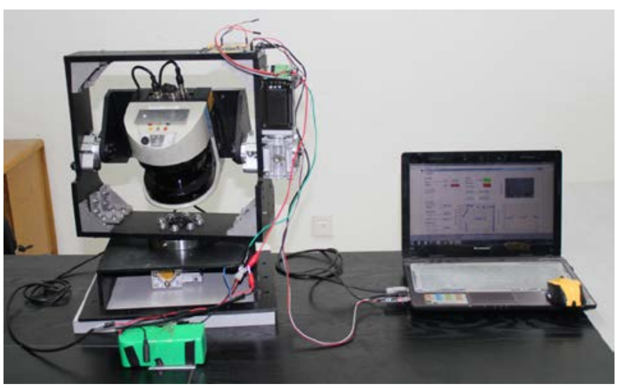


Fig. 1 information collection system based on two dimension laser scanner

In this paper, SICK LMS511 two-dimension laser scanner and FLUKE Ti55 infrared thermal imager were used to build an information collection system, as shown in Fig. 1. Two kind sensors were arranged in the same plane, which was convenient for data calibration, and installed in three tripod to adjust the position and angle, and it was connected to the host computer for data collection and control. Among them, the two-dimension laser rangefinder was used to obtain the obstacle position data, and the visible light image was used to extract the color and regional features of the image.

A. Original data collection

In the experiment, we collected each group data including two-dimension laser data, the original data was shown in Fig. 2.

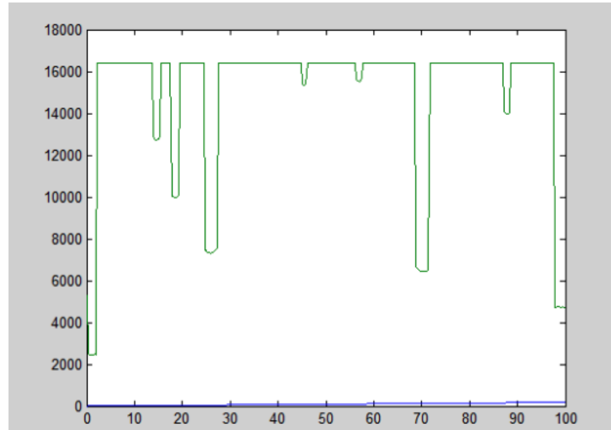


Fig. 2 The chart of 2d laser data

This research was based on the above data, after calibration, feature extraction and fusion data, the system can detect and identify the targets in forest adoptsthe.

B. Target feature extraction of laser data

Fig. 2 showed the environment information collected by the two-dimension laser scanner. Because the collected two-dimension laser data was a series of distance points, it was necessary to determine which points belong to the same target.

$$\|l_{i+1} - l_i\| = \Delta l \quad (i = 1,2,3,...) \tag{1}$$

In Eq. (1), l represented laser point i 's distance data. Through calculating the distance data difference Δl between each two adjacent points, it was used to determine whether the two adjacent points belong to the same target. When this value was more than a certain value, the two points didn't belong to the same goal, when it was less than the value, thinking the two points belong to the same goal, when a point adjacent distance was too large, thinking of the point was noise, removed it, here the threshold value was set as 200mm. Through the above algorithm, the laser point data can be extracted by clustering, and the results were shown in Fig. 3:

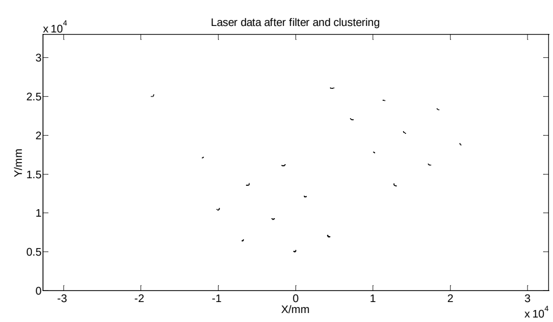


Fig. 3 Laser data after filtering and clustering

From Fig. 3, we can see that after filtering the data, the filter can remove the background data, acquire same target's laser points, and the position information.

III. Fuzzy Support Vector Machine Model for Multi-Class Gauss Kernel

Granulation of original data information by Gauss kernel, support vector machine training scale was reduced, some "noise points" of original sample effected on classification ability, improved the model learning efficiency and generalization ability in a certain extent. In practical applications, the training data of each support vector machine was different, the edge data was most easily misclassified, and more opportunity became support vector machine, and the intermediate data was into smaller probability as support vector. Therefore, in solving classification hyperplane process, the fuzzy theory was needed to describe the distribution of different training data, a membership function which is perpendicular to the classification hyperplane was defined u(0<u< 1), it expressed that each sample's importance of classification hyperplane, a plurality of membership functions together can be reduced non-separable region, so fuzzy support vector machine was constructed [18], the balance of slack variables ξ and penalty parameter C was completed, The objective function of seeking the optimal hyperplane was:

$$min_{w,b}\frac{1}{2}\|w\|^2+\mathrm{C}\sum_{j=1}^{l}u_j\xi_j \tag{2}$$
$$s.t. E_j^{'}(w^T W_j^{'}+b)\geq 1-\xi_j$$
$$\xi_j\geq 0, \mathrm{j}=1,2,...,l$$

Where W_j was the sample. The number of samples was m_j, for the general case, each particle was not the same in the samples, but satisfied $\sum_{j=1}^{l}m_j=n$, E_j was granularity label, to which information granules sample corresponding. In the fuzzy vector machine, grain weight was obtained through the membership function in each sample information, then the membership degree function selection and design was the key to establish the fuzzy vector machine model [19]. At present, there were many methods to construct membership function, but it was mainly based on the actual situation which needs to be solved. The most common membership model was based on the distance between sample and class center, then the membership degree was measured [20]. However, in the case that the performance of sample classification was not obvious, or the classification was more, it can not effectively describe the intermediate sample ownership problem. In this paper, on the basis of tradition membership calculation method, according to the distribution characteristics of samples in high dimension feature space, a new calculating membership degree formula was proposed. Two classes membership function was established, and two classes center points were obtained by using average value method, other sample points can be obtained from the Euclidean distance between positive and negative classes:

$$d^+(x_i)=\sqrt{\sum_{i=1}^{l}\sum_{j=1}^{10}\tau_j\left\|\phi(x_i)-\phi_{cen}^+\right\|^2} \tag{3}$$

$$d^-(x_i)=\sqrt{\sum_{i=1}^{l}\sum_{j=1}^{10}\tau_j\left\|\phi(x_i)-\phi_{cen}^-\right\|^2} \tag{4}$$

By comparing the Euclidean distance between sample points to the positive and negative class, the membership function was determined, it can be expressed by using half convex concave distribution:

$$u_i=\begin{cases} 1, d^+(x_i)-d^-(x_i)\geq \mathrm{a}+\frac{1}{\sqrt[k]{a}} \\ a[(d^+(x_i)-d^-(x_i))-\mathrm{a}]^k, a\leq d^+(x_i)-d^-(x_i)<\mathrm{a}+\frac{1}{\sqrt[k]{a}} \\ 0, -a<d^+(x_i)-d^-(x_i)<a \\ -a[(d^+(x_i)-d^-(x_i))-\mathrm{a}]^k, -(a+\frac{1}{\sqrt[k]{a}})\leq d^+(x_i)-d^-(x_i)<-\mathrm{a} \\ -1, d^+(x_i)-d^-(x_i)\leq -(a+\frac{1}{\sqrt[k]{a}}) \end{cases} \tag{5}$$

Where a was limit parameter, when the distance from sample to the negative class central was more than the threshold value $a+\frac{1}{\sqrt[k]{a}}$, then it was regarded as the positive class "useful points", the membership degree was 1, belonging to the positive class; when less than the threshold value $-(a+\frac{1}{\sqrt[k]{a}})$, it was regarded as the negative class "useful points ", the membership degree was -1, belonging to the negative class, when the distance from positive to negative class center, and the distribution of difference was in $[a,a+\frac{1}{\sqrt[k]{a}}]$, it was belonged to the positive class, but its contribution needed to calculated through membership degree, and the difference of two distribution center was in $[-(a+\frac{1}{\sqrt[k]{a}}),-a]$, it was belonged to the negative class, also needed to calculate the membership degree according to the distance; when calculating $[-a,a]$, it was regarded as "noise points", the membership degree value was 0, the subsequent FSVM training was reduced.

The Gauss particle kernel fuzzy support vector machine method to multi-class segmentation, there had been many scholars in the research, one mature method was a relatively one-versus-one, a SVM was designed between any two types in samples, K categories samples needed to design k(k-1)/2 SVM [21]. This method had high classification accuracy, but the classification function increases rapidly with the increasing of class number, which made the prediction process slow.

This method was improved in this paper, a directed acyclic graph (Directed Acyclic, Graphs, DAG) was used, the method was making several two class classifier with classification combination, and eventually constituted one multi-class classifier. In training phase, the same as one-versus-one method, for K class problem, DAG contained k (k-1) /2 two classifier. In the decision-making stage, starting from root node oriented acyclic graph was used, it contained K (k-1) /2 internal nodes and K leaf nodes, each internal node was a two class classifier, leaf nodes were the final value. On a test sample, from the root node to leaf node, according to the classifier output value, it decided the start walking through left or right path, until the leaf node, then samples belonging to the class value was obtained [22]. The training speed and one-versus-one method was same, but the decision speed significantly fast than voting one-versus-one method, directed acyclic graph was shown in Fig. 4:

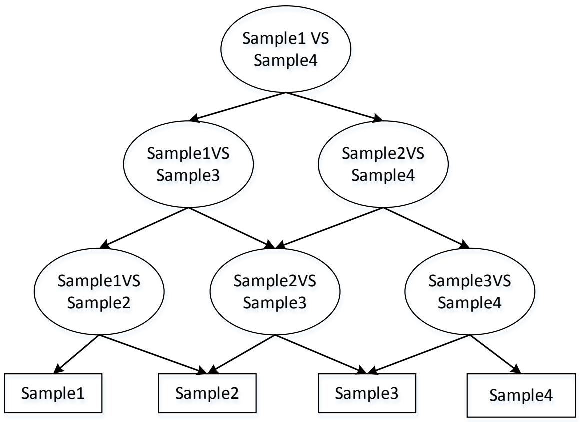


Fig. 4 Decision-making process of directed Acyclic Graphs

The above example was the using of support vector machine algorithm for two classification, when applied it to multi-class classification model, such as the sample set has 4 kinds samples. The first layer can be classified sample 1 and sample 4 to judge, the second layer was sample 2 and sample 4, sample 1 and sample 3, then the last third layer was sample 3 and sample 4, sample 2 and sample 3, sample 1 and sample 2 distribution, the decision classification results were obtained, the four class classification model was transformed to two class classification problem, although the obtained two class classifier number was the same with one-verse-one method, but the retrieval speed was fast. The second time, classification divided the sample 2 as the first class samples, sample 1 and sample 3 as second samples, directed acyclic quickly achieved results, enhanced the learning efficiency of SVM multi-class recognition, so the fuzzy support vector machine of multi-class Gauss particle (Multiclass Gaussian Granular Kernel Fuzzy Support Vector Machine, MGGK-FSVM) model was built.

IV. Improved MGGK-FSVM Model

In order to improve the recognition rate, this paper made an improvement on MGGK-FSVM, based on the size of Gauss kernel function, the parameter values for reasonable classification effect and penalty coefficient C were set. Through analysis Eq. (2), it can be found that, when β was too large, the training samples were all support vector, at this time it can be correctly identified, but prone to "over learning" phenomenon, the error identification of test samples was higher; when β was too small, tended infinitesimal, all the samples under the Gauss kernel support vector machine was the same, i.e. the classification ability is zero, tt identified all the sample points into same class. Similarly, the punishment coefficient will also affect the classification result, when C was too large, it will cause over learning, not suitable for promotion, when the C was too small, it will affect the generalization ability of classifier, all targets were tended to be one class. So choosing the appropriate C and β, it was helpful to optimize the algorithm. In this paper, a grid search method was used to achieve the optimal parameter selection method [23], we selected from the statistical view, the specific methods were as follows:

(1) First, C and β were given value range, values were in the form of 2^n, the different groups C and β values were divided into the grid.

(2) Second, then searching each grid value, the classification results were calculated for each classifier grid values; if there was many groups (C and β values) that able to make the highest recognition rate, then the smallest penalty coefficient was selected as the best parameters, avoiding over learning phenomenon, and finally the C and β values corresponding to the optimal classification results were selected as the optimal solution.

Through the above method, C and β values were selected by Eq. (2), and the final classification result was obtained.

V. Experiment results and analysis

This experiment used three kinds of target, trees, people, fire. The sample space data was 1000 groups, 200 randomly samples were selected each time, and collection 180 samples were taken as training set, remaining 20 samples were taken as test set in each group. In order to facilitate comparison, this paper compared the MGGK-FSVM classifier and SVM classifier. In order to test the results correctness and recognition accuracy, we will repeat several experiments. In the experiment training, we set the penalty coefficient C=2 in objective function, Gauss kernel coefficient β =0.01, membership parameters: a=1, k=2. The model formula was taken into samples points to calculate, and the multi-class Gauss kernel fuzzy support vector machine classifier was implemented. The results were shown in Table 1:

Table 1 Classification result with MGGK-FSVM

Serial number	Tree identification	Pedestrian recognition	Fire identification	Correct rate
1	20/20	20/20	18/20	96.7%
2	20/20	19/20	16/20	91.7%
3	18/20	18/20	15/20	85%
4	19/20	20/20	16/20	91.7%
5	20/20	19/20	17/20	93.4%
6	20/20	20/20	16/20	93.3%
Mean	97.5%	96.7%	81.7%	**92%**

From Table 1, we can see that three kinds of target recognition in experiment environment. The classification model can identify the target, all recognition object average recognition rate was 92%, it can be seen from the Table 1, the highest recognition rate was trees, and it can reach 97%, and the lowest identification rate of fire was only 81.7%, this is because the trees and people all belonged to static, the objective function $F(x)$ was solved quickly and efficiently in the algorithm, the weight (w) calculating was simple, but the fire image was a dynamic feature map, Eqs.(3),(4) Euclidean distance $d^+(x_i)$, $d^-(x_i)$ were straight dynamic changing, solving objective function $F(\mathrm{x})$ needed to recalculate each time, which causing error larger, the corresponding results would produce a certain deviation, in order to further verify the MGGK-FSVM algorithm, we taken SVM algorithm as comparison.

Table 2 Classification results of different models under experiment environment

Serial number	Time (s)	Tree identification	Pedestrian recognition	Fire identification	Correct rate
SVM	8.75	96%	93%	78%	89%
MGGK-FSVM	7.24	97.5%	96.7%	81.7%	92%

It can be seen from Table 2, different classification algorithm identifing the target was different under experiment environment, because the linear SVM was a relatively good classification method in tradition two class classifier, so this paper used SVM comparing with MGGK-FSVM. As can be seen in Table 2, the proposed Gauss granularity and the new membership function, can effectively remove the noise points in sample space, improve the success rate of target classification. And MGGK-FSVM running time was shorter than SVM. Single learning time was about 7 seconds, and its computation complexity was low, the graph acyclic multi-class recognition improved learning efficiency. Because trees, people had better laser and visual features, so various classification algorithms had the separability, and this paper identification of fire source was obviously improved, i.e.MGGK-FSVM recognition algorithm. It can reach 81.7%, it had a great progress for general recognition algorithm, which meant that the model had correct recognition ability for forest fire.

In addition, we conducted experiments on the improved MGGK-FSVM algorithm, C and β values did not set as default value, initially, we first set the range of penalty coefficient as $2^{-5} \sim 2^{5}$, Gauss particle kernel parameter β 's range $2^{-5} \sim 2^{5}$, the step of C and β was 2,and the sample data will be divided into 20 parts for training and testing, the improving MGGK-FSVM algorithm optimization of two parameters results were shown in Fig. 5:

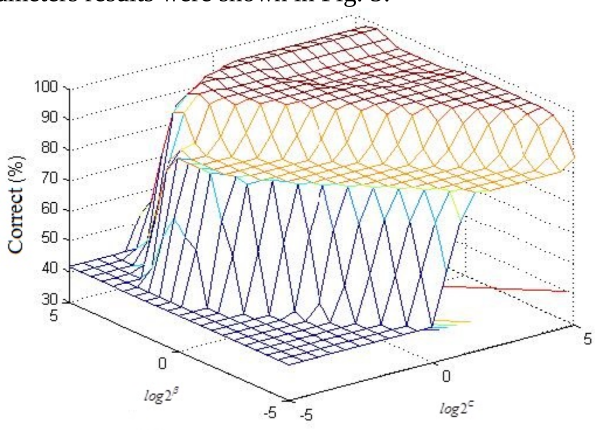


Fig. 5 Result of optimal parameter choice

In Fig. 5, the horizontal axis was $log2^{C}$ value, the longitudinal axis was $log2^{\beta}$ value, the vertical axis represented the correct recognition rate, after several times of training and testing, the optimal parameters were: C =0.3417, $\beta = 0.0078125$. After determining the parameters, the above experiment C and β values were replaced, and re-executed the above experiment again, the improved MGGK-FSVM model can improve the correct recognition rate to 96%. Finally, on the basis of research, trees, people, fire sources were identified, and through the PC software with color difference, the blue box was the trees, people was used red logo, and black box was fire, as shown in Fig. 6.

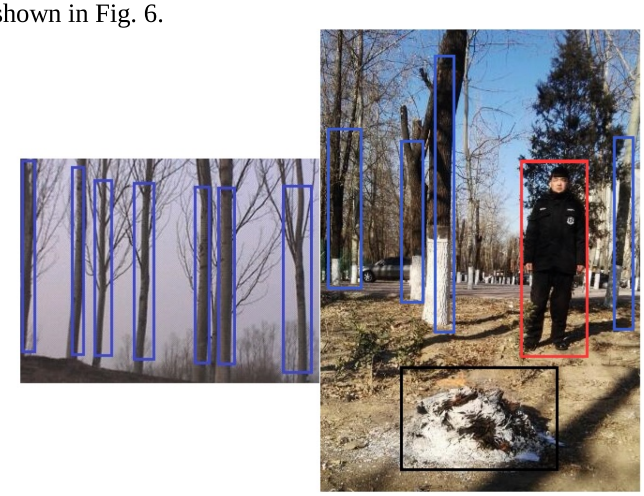
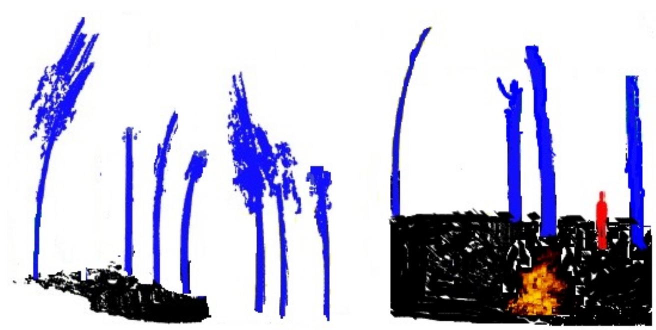


Fig. 6 Recognition result for different targets

It is the classification of trees, people, fire sources in the scene in Fig. 6, the same language implication object can be divided into the same class in point cloud data.



(a) (b)

Fig. 7 Final classification results of fused point cloud in scene first(a) and second(b)

In Fig. 7, different color showed different result in same scene. The ground was black, person was red, trees were blue. The fire source was yellow, as can be seen from the Fig. 7, the trees were the largest sample, Fig.(a) there had 7 trees, , Fig.(b) had 1 tree, 1 people, accompanied by fire. It was clear from Fig. 7 that different objects can be classified in forest environment. The results can provide effective reference for forest workers and reduce operation risk.

VI. Conclusion

According to the forest environment independent object semantic classification problem, the image data after segmentation and 3D laser point cloud data were used, artificial forest within adoptsthe target and obstacles color, shape, intensity and reflection characteristics was extracted in three-dimension space, based on linear support vector machine classifier, the Gauss kernel was imported to enhance the fuzzy support vector machine, the membership function was proposed based on the distribution of concave and convex distribution, decision directed acyclic graph method was used in multi-class classification application. Through a large number of samples in training and learning under the plantation environment, this method was proved better than SVM model classification, it can effective identify the trees, pedestrians, fire under experiment environment, after model parameters optimization, comprehensive average correct recognition rate can reach 96%, this can provide driver accurate forest target recognition results.

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