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A Novel Identification Method of Obstacles Based on Multi-sensor Data Fusion in Forest

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Abstract: In this paper an obstacle identification system was set up and an artificial neural network (ANN) was established to identify obstacles in forest based on multi-sensor fusion, aiming to improve the efficiency of automated operations of forestry harvester in the complicated environment of forest areas. Firstly, a 2D laser scanner and an infrared thermal imager were used to collect the information of obstacles in forest areas. Based on the collected infrared photo, visible pictures and laser scan data, image fusion and data association were conducted to obtain features of obstacles. Second, a BP neural network was established for forest obstacles identification by training samples. Then, to improve the performance of BP model, several common used functions were adopted to construct BP model by permutations and combinations. The test results showed that the model with trainlm training function had a best performance in forest obstacles identification. Finally, three best models were selected to be evaluated by testing all samples and the results illustrated that the three selected BP neural network models can identify trees, people, stones at a high correct rate of 93.3 % or more.

Keywords: Laser scanner, Infrared image, Visible image, Multi-sensor data fusion, Obstacle identification.

1. Introduction

In order to meet the needs of the rapid development of forestry, automation and high efficiency for forestry equipment are desired. However, various obstacles and the complicated environment in forest will lead to intermittent operations and driving dangers for forestry equipment [1]. Therefore, it is necessary to develop a highly efficient obstacle identification method in forest areas.

Regarding the obstacles identification, various research works have been done, in which different kinds of sensors are used as tools. L. Y. Chang designed an optical system of visible light detection camera to realize the detection of dark and weak target in space [2]. Mendes, A. used a laser range finder to detect and track moving objects. It cannot only classify several kinds of objects but also detect new ones [3]. Navarro-Serment L. E. employed three-dimensional LADAR measurement on a moving vehicle to detect and track pedestrians over time [4]. Sume, A. utilized a stepped-frequency radar to detect moving objects based on Doppler-based techniques [5].

Based on the above, camera, laser scanner, and radar are commonly used tools in obstacles detection. But one single sensor cannot collect full information of object. And multi-sensor fusion technology can solve this problem. Sensors can complement each other to make use of information effectively and obtain accurate results. How to fuse the information derived from different sensors is the focus of our study.

So far, multi-sensor fusion technology has been used in many areas including: image fusion [6-7], intelligent robots [8-9], remote sensing [10], fault diagnosis [11], and pattern recognition [12-13]. In obstacles identification, it is mainly used in vehicle system and robot movement. Raphaël Labayrade achieved real time-detection of multi-obstacles in the automotive context based on the fusion between stereovision and laser scanner [14]. Broggi, A. developed a pedestrian-detection system with fusion of a laser scanner and a vision system to localize pedestrians in front of the vehicle [15]. X. Z. Zhang and R.C. Luo both used sensor fusion strategy to realize simultaneous localization and mapping for robots [16-17]. Baltzakis H. employed laser and visual data for robot motion planning and collision avoidance [18].

However, the sensors fusion technology has not been used in forest obstacles identification. In the study on the forest environment, researchers have used terrestrial laser scanning (TLS) and airborne laser scanning (ALS) as main tools to acquire detailed parameters of standing trees and differentiate tree species from air. Based on using TLS and ALS, many researchers have proposed various algorithms to determine the tree parameters like position and diameter at breast height (DBH). X. Liang et al [19] developed a fully automatic stem-mapping algorithm by using single-scan TLS data to collect individual tree information from forest plots. Jari Vauhkonen et al [20] used six different algorithms to extract treetop position and estimate tree height. The performance of all algorithms were compared and analyzed. Eva lindberg et al [21] proposed a new method to measure tree stems automatically by terrestrial laser scanning (TLS), and to further link these ground measurements to ALS data analyzed at the single tree level. Leeuwen M. et al [22] presented an efficient and robust method for stem detection from terrestrial laser scanning based on the Medial Axis Transformation. Brolly G. et al [23] introduced a method to extract individual tree parameters including tree location, DBH, and tree height by constructing a digital terrain model and a digital crown surface model.

Although researchers have used laser scanner to measure detailed parameters of standing trees, one single sensor cannot satisfy the requirement of obstacles identification due to complex environment and insufficient light in forest. Therefore, an obstacle identification method based on multi-sensor fusion is proposed in this paper.

First, a 2D laser scanner and an infrared thermal imager were used to collect the information of obstacles in forest areas. Based on the collected infrared photo, visible pictures and Laser scan data, image fusion and data association were done to obtain 6 features of obstacles: R, G, B, aspect ratio, rectangularity, and temperature. Second, a BP neural network was established for forest obstacles identification by training samples and it had a correct rate at 90.00 % for one test. Next, to improve the performance of BP model, several common used functions were adopted to construct BP model by permutations and combinations. The test results showed that the model with trainlm training function had a best performance in forest obstacles identification. Finally, three best models were selected to be evaluated by testing all samples and the results illustrated that the three selected BP neural network models can identify trees, people, stones at a high correct rate of 93.3 % or more.

2. Obstacle Identification System

2.1. Flowchart of Proposed Method

Fig. 1 illustrates the technical flowchart of the obstacle identification system developed in this research. The system functions in the following procedure:

1) Collection and Pre-processing of the data by a laser scanner and an infrared thermal imager;
2) Extract features of obstacles from the laser data and images;
3) Obtain the region of interest (ROI) by data association of the laser points and the images;
4) ANN model construction by training samples;
5) Select the transfer function and the learning function to construct ANN model with high identification correct rate and low errors.
6) Finally, test all samples with selected model.

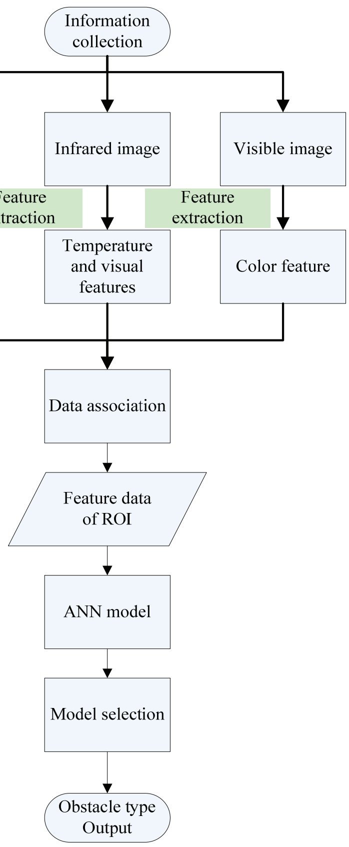

Fig. 1. Flowchart of the proposed method.

2.2. Test Equipment and Placement

Obstacles information is collected by a 2D laser scanner and an infrared thermal imager. As shown in Fig. 2, both the devices were placed on the same horizontal plane in this experiment conducted in Beijing Bajia Contry Park.

Fig. 2. Sensors placement in this experiment.

2D laser scanner LMS291 from SICK Inc. within the scan range of 32 m with a field of view (FOV) of 100° and angular resolution of 0.25°, is a non-contact measurement system, which detect two-dimensional space around as laser radar. Its operating temperature is between 0 ^{0}C-50 ^{0}C, and is an active scanning system that does not require external passive components. This makes it particularly suitable for the transport system and vehicle control.

The infrared thermal imager FLUKE Ti55 is used to capture the image of both visible light spectrum and infrared light simultaneously. Its image resolution is 240×320. It adopts a Fluke IR-Fusion technology to put the visible and infrared images fused. So it can speed up and facilitate the subsequent data acquisition process.

3. Obstacle Identification Approach

3.1. Information Extraction from Laser Point Data

The 2D laser scanner used reflected echo of the scanning laser to detect obstacle. The scanning data was a series of points that represented the distances between the obstacles to the scanner. How to distinguish and recognize these points from different objects was very important. Therefore, data filtering and obstacle data extraction were performed to classify the laser points into different segments for the corresponding objects. An edge detection method was adopted to calculate laser point clusters, which was described as follows: Calculated the distance of two adjacent laser points in the y-axis. If the distance value was smaller than a threshold, the two points were considered to belong to the same object. If not, they were separated. Additionally, a laser point that is far from its adjacent points was considered as a noise variable and excluded for further analysis. Only the clusters with a certain size were retained.

In this way, a large number of laser points were excluded and a group of candidate obstacles were obtained. Then, the information of each object including the depth, width, and the location in the laser coordinate system can be obtained from laser data.

3.2. Information Extraction by Visible-infrared Image Fusion

3.2.1. Image Fusion by PCNN

Both visible and infrared images were used in obstacle observation and obstacle feature extraction, but both of them were subject to the influence of different environmental conditions and had their own disadvantages. To improve obstacle detection in the forest environment, a pixel-level image fusion algorithm for visible-infrared images was used. It enhances clarity and analyticity of pictures and emphasizes the feature information of the target.

In this paper, PCNN (Pulse Coupled Neural Network) was adopted to complete the fusion of visible-infrared images. PCNN is a mathematical model inspired by the study of the cat nervous system, so it has a biological basis when used for image processing. The neurons represent the pixels in the image, and the luminance pixel value corresponds to an external stimulus signal. Each pixel is connected to the surrounding pixels with range of 3 × 3 or 5 × 5. PCNN model has properties of synchronous pulse excitation and dynamic pulse distribution. When used in image processing, the sync pulse excitation allows the area information, edge, texture with the similar brightness in the image excited simultaneously; on the other hand, dynamic impulses can obtain pulsed images at different times, forming time series excitation diagram. The characteristics of the original image can be extracted with the invariance of displacement, scale, rotation and distortion.

By merging visible-infrared images by PCNN, sharper edges of the obstacles in the images can be obtained, which provided useful information for feature extraction.

3.2.2. Features Selection from Visible-Infrared Images

To identify the obstacles in the images, the features of the objects were extracted based on image fusion (Fig. 3). The most common obstacles in the forest environment are trees, rocks and human, and the characteristics need to be found to represent each of the three categories with independence and discrimination. Therefore, a number of features such as the temperature, color, aspect ratio, and rectangularity were chosen for feature extraction from images.

Fig. 3. (a) Infrared Image.

Fig. 3. (b) Visible image.

Fig. 3. (c) Fusion image.

1) Temperature is an important feature for distinguishing obstacles because the texture of the objects in each category is different. Therefore, the obstacle temperatures were calculated according to the infrared temperatures using a comparison table.
2) Colors were obtained from visible images and expressed in red-green-blue (RGB), and a 3-vector was used to match each color feature.
3) Aspect ratio is the ratio of width and height of the obstacles. The aspect ratio describes the obstacle shapes and can distinguish between slender objects and round or square objects.
4) Rectangularity is the ratio of obstacle areas and its minimum enclosing rectangle (MER) areas. The rectangularity reflects the proximity degree of an object with its MER and it can be used as a standard for distinguishing trees and other objects.

3.3. Data Association between Laser Points and Images

In order to make full use of the information acquired by each sensor, laser data need to be associated with images so that it can describe which object the features belonging to. In this research our goal is to study the static information fusion algorithm, so a simple data association is adopted to get the region of interest [24].

Software settings make laser scanner and infrared thermal imager synchronous to ensure the consistency of the time. Ignore the error caused by the sensors center position deviation, then, data association can be achieved as shown in Fig. 4.

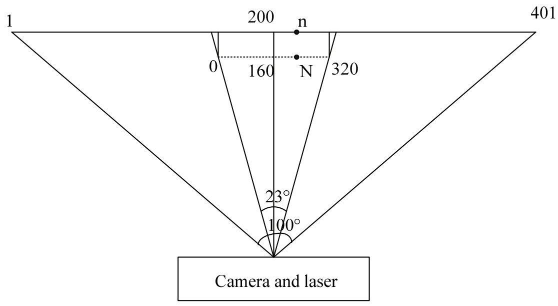

Fig. 4. Illustration of the data association.

In Fig. 4, laser scanner and infrared thermal imager are on the same center position with the same height. The FOV of the laser scanner and infrared thermal imager are 100" and 23" respectively. *N* represents the pixel number of the row in a picture and *n* is the number of laser points in one scan. Then the relationship of laser points and image can be described by calculating the laser points and the pixel number corresponding to 1 degree. After that, objects in laser and image could be associated to find the ROI.

3.4. ANN for Obstacle Identification

After the ROI in an image was obtained, an ANN model was used for obstacle identification based on 6 features derived from laser points and visible-infrared images.

ANN is a mathematical model applying structures that similar to the brain synaptic couplings to achieve information processing. BP (Back Propagation) neural network is a common neural network learning algorithm, which is a hierarchical neural network, composed of an input layer, an intermediate layer and an output layer. The intermediate layer can be extended to multiple layers. The neurons between adjacent layers are fully connected, and that in each layer have no connection.

From the Fig. 5, in the three layers, the input vector is $X=(x_1,x_2,...x_i,...x_n)^T$; the output vector of hidden layer is $Y=(y_1,y_2,...y_j,...y_m)^T$; the output vectors of output layer is $O=(o_1,o_2,...o_k,...o_l)^T$; and the desired output vector is $d=(d_1,d_2,...d_k,...d_l)^T$. The weights matrix between the input layer to the hidden layer is $V=(v_1,v_2,...v_j,...v_m)^T$, where the column vector V_j is the weight vector corresponding to the j-th neurons in hidden layer; and the weights matrix between hidden layers to output layer is $W=(w_1,w_2,...w_k,...w_l)^T$, where the column vector W_j is the weight vector corresponding to the k-th neurons in output layer.

When the output signal does not match with the teaching signal, there is output error E:

$$E=\frac{1}{2}(\mathbf{d}-\mathbf{o})^2=\frac{1}{2}\sum_{k=1}^{l}(d_k-o_k)^2 \tag{1}$$

Expand the above formula to the hidden layer

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{l}\left[d_k-f(net_k)\right]^2 \\ &= \frac{1}{2}\sum_{k=1}^{l}\left[d_k-f\left(\sum_{j=0}^{m} w_{jk}y_i\right)\right]^2 \end{aligned} \tag{2}$$

Expand the above formula to the input layer

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{l}\left\{d_k-f\left[\Sigma_{j=0}^{m} w_{jk} f(net_j)\right]\right\}^2 \\ &= \frac{1}{2}\sum_{k=1}^{l}\left\{d_k-f\left[\Sigma_{j=0}^{m} w_{jk} f\left(\sum_{j=0}^{n} v_{jk}x_i\right)\right]\right\}^2 \end{aligned} \tag{3}$$

As can be seen from the above equation, the output error E is the function of network weights w_{jk} , v_{ij} of each layer, so the weights can be changed to adjust the error E. The purpose is to adjust the weights to decreases the error continuously, so the weight adjustment amount should be proportional to the error gradient descent. Therefore, BP neural network is called error gradient descent algorithm.

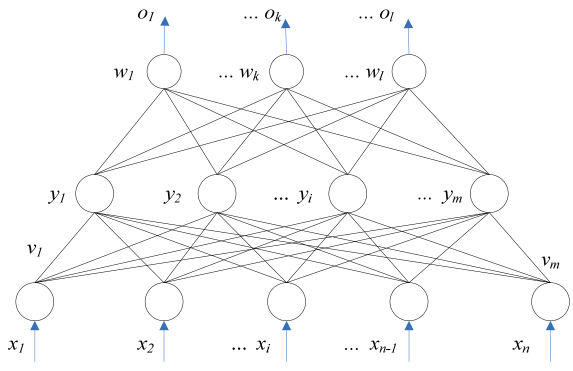

Fig. 5. BP neural network model.

4. Experiments and Results

The aim of this study is to identify the obstacles in the forest according to the acquired obstacle characteristic information. Applying MATLAB software to carry on simulation of BP algorithm, we can find a suitable BP network model to distinguish between the types of obstacles. There are six kinds of obstacle features including RGB values, temperature, aspect ratio, rectangularity, which are considered as inputs. And three types of obstacles that people, trees, and stone are outputs.

Then the BP network can be established as follow:

1) Input layer has 6 neurons.
2) Nodes in the hidden layer is set to 12 according to the number of training samples and the dimension of the input and output layer
3) The dimension of output layer number is equal to the number of the obstacle types 3. Construction principle of the output layer is that the output in the position corresponding to different types is 1, and the rest position is 0, such as trees [1,0,0], people [0,1,0], stone [0,0,1].
4) Tansig-tansig is selected as the network error transfer function.
5) Powell-Beale connection gradient BP training function traincgb is selected as learning function.
6) The number of learning is set to 500 times; the learning rate is set to 0.0005; and the training target is set to 0.001.

In this research, 150 samples including 50 trees, 50 peoples and 50 stones have been collected. Randomly use 120 samples to train the network and test the remaining 30 samples. Evaluate the obstacle classification capabilities of BP Network based on the correct rate and mean square error. One test result is shown in Table 1.

Table 1. One test result of the BP network for obstacles identification in forest.

yT =									
0.9684	0.9712	0.9577	0.9663	0.9722	0.9721	0.9721	0.9721	0.9687	0.9676
0.0885	0.0245	0.2767	0.1314	-0.0027	0.0033	0.0039	0.0045	0.0279	0.0058
-0.0611	-0.061	-0.0569	-0.0602	-0.0581	-0.061	-0.0613	-0.0615	-0.0219	0.0106
Tree	Tree	**Invalid**	**Invalid**	Tree	Tree	Tree	Tree	Tree	Tree
0.0009	0.0038	0.0007	0.0008	0.0289	0.0304	0.0008	0.0008	0.0007	0.0027
0.9926	0.9925	0.9926	0.9926	0.992	0.992	0.9926	0.9926	0.9926	0.9925
-0.0028	-0.0028	-0.0027	-0.0027	-0.0032	-0.0026	-0.0027	-0.0028	-0.0026	-0.0027
People	People	People	People	People	People	People	People	People	People
-0.0208	-0.021	0.0113	0.0163	0.3197	-0.02	-0.0199	-0.0189	-0.0201	-0.0201
0.0011	0.0005	-0.0002	-0.0002	-0.0007	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
0.9678	0.9674	0.9648	0.9645	0.9353	0.9669	0.9669	0.9668	0.9669	0.9669
Stone	Stone	Stone	Stone	**Invalid**	Stone	Stone	Stone	Stone	Stone

Mean square error of the testing results is 0.0939. From Table 1 it can be seen that there are three invalid outputs, so obstacle classification accuracy of BP neural network model is 90.00 %. But the mean square error of the testing results is large, so it is need to adjust the parameters, learning function and the error transfer function to improve the BP model.

Aiming to obstacle classification problem, there are three error transfer functions: S-type logarithmic function logsig, S-type tangent tansig, pure linear function purelin can be used in BP model construction. Furthermore, common used learning functions are Levenberg-Marquardt BP training function trainlm, adaptive learning rate gradient descent BP network training function traingda, momentum and adaptive learning rate BP gradient descent training function traingdx, Powell-Beale continuous gradient BP training function traincgb.

By permutations and combinations of these functions, it can form a variety of BP network models. Evaluate the performance of the BP neural network according to the training times, the training mean square error, the test mean square error and the identification correct rate four indicators. By calculation and contrast, it is found that the model with the trainlm training function performed best. The contrasts of all models with trainlm training function are shown in Table 2.

Table 2. The contrasts of all models with trainlm training function.

Transfer function \ Indicators		Model number	Training times	Training mean square error	Test mean square error	Identification correct rate (%)
logsig	logsig	①	46	5.5e-2	0.7307	73.33 %
tansig	logsig	②	10	6.2e-5	0.4108	83.30 %
purelin	logsig	③	—	—	—	—
logsig	tansig	④	39	6.5e-5	0.0250	96.67 %
logsig	purelin	⑤	42	6.7e-5	0.0853	96.67 %
tansig	tansig	⑥	32	4.9e-6	0.1990	93.33 %
tansig	purelin	⑦	54	9.6e-5	0.0584	96.67 %
purelin	tansig	⑧	—	—	—	—
purelin	purelin	⑨	—	—	—	—

In the above table 2, model ③, ⑧, ⑨ cannot have a correct output for BP network; model ①, ② have a relatively low correct rate; the correct rate of model ⑥ is relatively high, but the test error is also high. In model ④, ⑤, ⑦, the mean square error is within 10% of the requirements and the identification correct rate is relatively high, so model ④, ⑤, ⑦ can be adopted as BP model to identify obstacles in forest.

To sum up, select logsig or tansig as the transfer function from output layer to the hidden layer, tansig or purelin as the transfer function from hidden layer to the output layer, and trainlm as the learning function for BP network model, which is suitable for obstacles classification and identification in forest.

Next, BP model ④, ⑤, ⑦ are considered as model I, II, III, then they are evaluated by testing all the 150 samples data. The training performance and the test indicators are shown in Fig. 6 and Table 3 respectively.

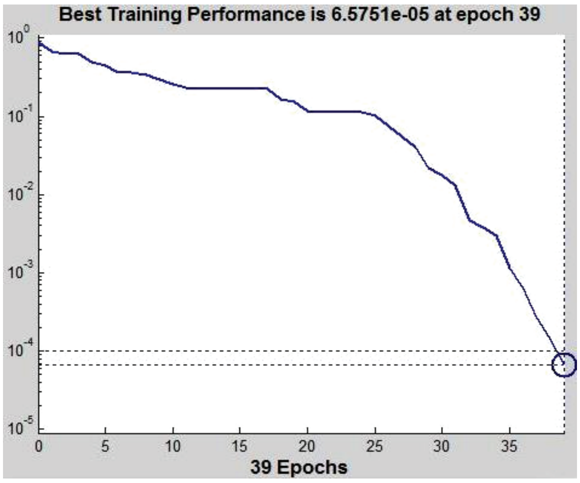

Fig. 6. (a) The training performance of model I.

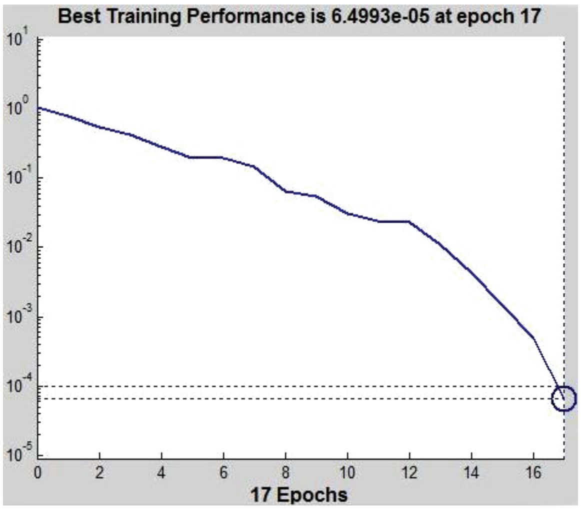

Fig. 6. (b) The training performance of model II.

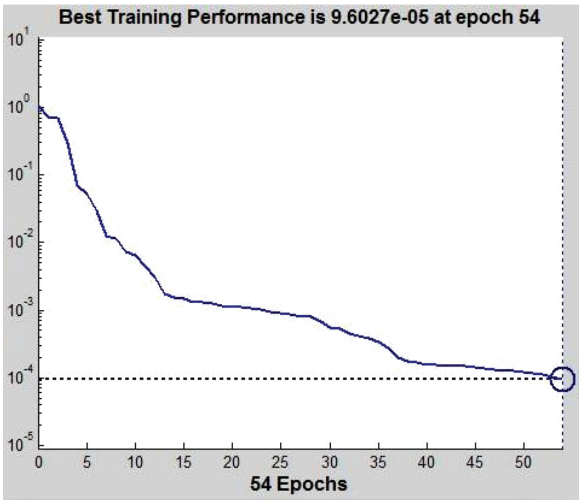

Fig. 6. (c) The training performance of model III.

Fig. 6 showed that the three models can reach the predetermined target value in a short training time, so they had a good learning performance.

Table 3. The contrasts of three BP model with testing all samples.

BP Model	Training times	Training mean square error	Test mean square error	Correct rate (%)
Model I	39	6.6e-5	0.0166	96.6 %
Model II	17	6.5e-5	0.0396	93.3 %
Model III	54	9.6e-5	0.0296	96.6 %

It can be seen that the three BP neural network models can identify trees, people, stones at a high correct rate based on the 6 features of the three common obstacles in forest. The correct identification rate can be up to 93.00 % or more, and the mean square error of the test less than 5 %. By testing and selecting, three BP models that suitable for obstacles identification in forest are obtained. It shows that the structure of the BP neural network model is reasonable, and the overall performance is also good.

5. Conclusions

In this paper, firstly, a 2D laser scanner and an infrared thermal imager were used to collect the information of obstacles in forest areas. Based on the collected infrared photo, visible pictures and Laser scan data, image fusion and data association were conducted to obtain 6 features of obstacles: R, G, B, aspect ratio, rectangularity, and temperature. Second, a BP neural network was established for forest obstacles identification by training samples and it had a correct rate at 90.00 % for one test. Next, to improve the performance of BP model, several common used functions were adopted to construct BP model by permutations and combinations. The test results showed that the model with trainlm training function had a best performance in forest obstacles identification. Finally, three best models were selected to be evaluated by testing all samples and the results illustrated that the three selected BP neural network models can identify trees, people, stones at a high correct rate of 93.3 % or more.

The current obstacle detection method was proposed on the basis of a static system. In the future, dynamic obstacle detection will be studied in order to achieve real-time and rapid detection of obstacles in the forest environment.

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