

Obstacles Detection Algorithm in Forest based on Multi-sensor Data Fusion

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Abstract—In this paper an obstacle detection system was set up and a novel algorithm was proposed to detect obstacles in forest, aiming to improve the efficiency of automated operations and reduce the risk to cause the accident of forestry harvester in the complicated environment of forest areas. First a 2D laser scanner and an infrared thermal imager were used to collect the information of obstacles in forest areas. Second the features of each obstacle including temperature, color, aspect ratio, and rectangularity, were extracted from the laser points, visible images and infrared images. Then, we use the sample feature data to train a support vector machine (SVM) for object identification. The experiments were conducted on the various obstacles and the experimental results showed that the proposed algorithm was effective and provided a computation basis for automated operations of harvester.

Index Terms—Laser Scanner; Infrared Image; Visible Image; Multi-Sensor Data Fusion; Obstacle Detection

I. INTRODUCTION

Automation and high efficiency of forestry equipment are required to meet forestry development demands. However, the forestry equipment is difficult to operate in forest areas because of various obstacles and the complicated environment [1]. Additionally, light in the forest is insufficient, leading to intermittent operations and driving dangers. Therefore, it is necessary to develop a highly efficient obstacle detection method in forest areas.

There has been a great amount of work on obstacle detection and different kinds of sensors in tools, such as cameras, laser scanners, radar range finders and sonar range finders, have been used to detect obstacles. The information collected by a single sensor is limited and is not accurate enough, therefore multi-sensor data fusion is considered in order to improve the performance of obstacle detection. Multi-sensor data fusion brings significant advantages over single-source data from a single sensor to increase the robustness and confidence of sensor applications [2-3]. By using an active sensor and a vision system, many researchers proposed fusion approaches, for instance, a radar with mono-vision [4], a laser scanner with a camera [5], a stereovision rig [6].

As regards to obstacle detection, the multi-sensor data fusion technology is mainly used in vehicle systems [7], robots [8] and building detection [9]. At the same time, a fast and robust sensor fusion algorithm is also required.

Many researchers focus on developing a data fusion algorithm to achieve higher speed and accuracy. There are three main categories of the algorithms: the first is operating directly on data source like weighted average method and artificial neural network (ANN); the second is based on statistical characteristics and probability model, such as the Kalman filter method, Bayesian estimation, and statistical decision theory; and the third is the fuzzy reasoning and evidence reasoning developed on the basis of rule reasoning. Currently, Bayesian inference [10-11], Dempster-Shafer evidence theory [12], ANN [13], and support vector machine (SVM) classifier [14] are popular and mainly used in researches. The first two methods can detect objects with a combination of different data sources and cover uncertain information but need the analysis of a prior probability which is difficult to obtain. ANN and SVM are more accurate in pattern recognition due to their adaptive learning ability. Compared with ANN, SVM has a better classification effect and can overcome the disadvantages of ANN, such as the "over-learning" problem.

With the development of advanced technology, in the study on the forest environment researchers have used terrestrial laser scanning (TLS) as a main tool for acquiring detailed information about the parameters of standing trees. Based on using TLS, many algorithms were proposed for determining the tree parameters like the position and diameter at breast height (DBH). M. Simonse [15] described an automatic algorithm, which used Hough-transformation and circle approximation to detect a tree stem based on digital terrain model (DTM). On the basis of M. Simonse., T. Aschoff [16-17] added an ellipse fitting algorithm to combine circles and trees to check the results with linear regression. G. Király and G. Brolly [18-19] proposed a clustering method and the so-called crescent method to determine the height of a tree. Yili Zheng used a laser scanner to measure trees for timber harvest operations using the Fletcher-Reeves conjugate gradient algorithm [20]. Although many researchers have used laser scanners to detect and measure trees in forest, the multi-sensor technology has not been widely applied to detect obstacles in forest area. Moreover, the current methods cannot achieve the purpose of object identification depending on only the data from a single sensor in the complicated environment of forest areas. Therefore, the multi-sensor technology is introduced in this paper for obstacle recognition.

Firstly, the obstacle information is collected from the laser points using a 2D laser scanner. Besides, visible and infrared images of the obstacles are obtained simultaneously through an infrared thermal imager. After that, an edge detection method is adopted to calculate laser point clusters and laser features of candidate obstacles such as width and location can be obtained. Next, image fusion was done to acquire the image features of the objects such as the height, width, shape, temperature and color. Furthermore, regions of interest (ROI) are obtained by association of the laser points and the images. Finally, an SVM algorithm is used to achieve ROI recognition by sample features training. The experimental results have shown that this method has an accurate recognition effect.

II. OBSTACLE DETECTION SYSTEM

A. System Hardware

In this research, obstacle information was extracted from a laser scanner and an infrared thermal imager. 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°, was adopted to measure the detailed data of the obstacles such as the depth and width. Besides, the infrared thermal imager FLUKE Ti55 was used to capture the image of both visible light spectrum and infrared light simultaneously. So temperature, color, shape, and other visual information of the obstacles all could be obtained from visible and infrared images. Both the devices were placed on the same horizontal plane for data collection and their heights and angles were adjusted by a tripod.

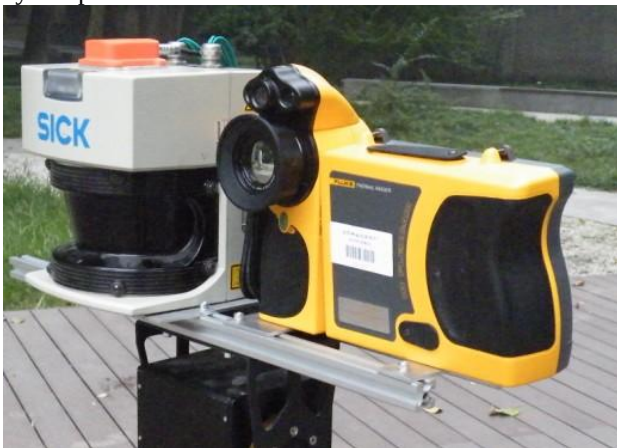


Figure 1. Sensors placed on the same horizontal plane in this experiment

B. Technical Flowchart of the System

Figure 2 illustrates the technical flowchart of the obstacle detection system developed in this research. The system functions in the following procedure:

- (1) Pre-processing of data extracted from laser points as well as visible and infrared images
- (2) Features extraction from the laser data and images
- (3) Region of interest (ROI) obtaining by associate the laser points with the images

- (4) SVM model construction by feature recognition training

Finally, a decision is made so that the ROI can be identified and located.

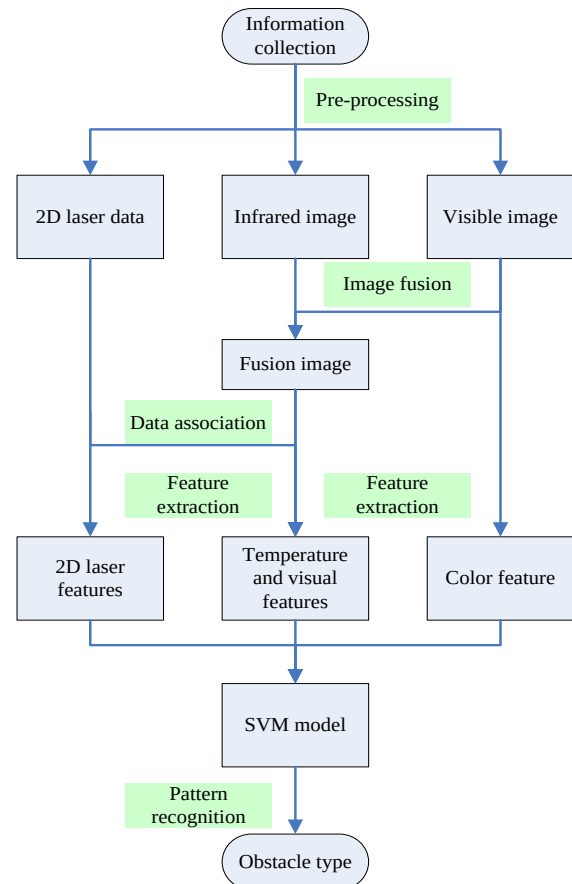


Figure 2. Technical flowchart of the obstacle detection system

III. OBSTACLE DETECTION APPROACH

A. Feature Extraction from Laser Point Data

When the scanning laser met an obstacle, an echo was reflected back to the scanner. The scanning data was a series of points that represented the distances between the obstacles and the scanner and 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.

Figure 3 shows the laser data by one scan. An edge detection method is adopted to calculate laser point clusters, which is described as follows:

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

where l_i refers to the distance from a laser point to the scanner. The distance Δl between l_i and l_{i+1} was calculated using the above formula. If the calculated value was smaller than a threshold, the two points were considered to belong to the same object. If not, they belonged to separated objects. In addition, a laser point that was 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. A result of laser point data processing is shown in figure 4. The features of each object were extracted from the laser point data, which included the detailed information of the depth and width of the object and the location in the laser coordinate system.

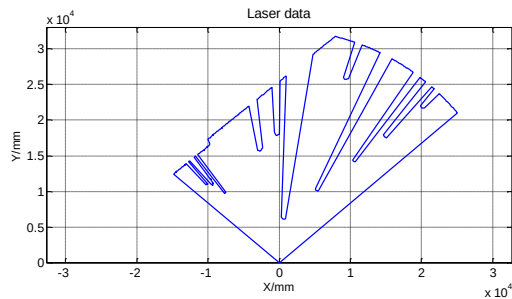


Figure 3. Laser data before pre-processing

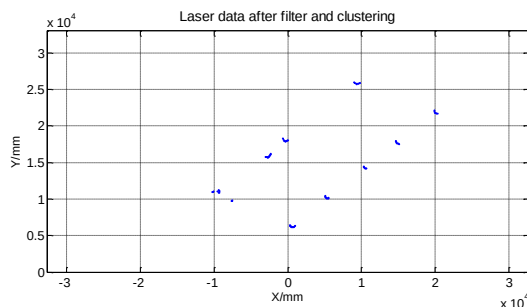


Figure 4. Laser data after filtering and clustering

B. Feature Extraction by Visible-infrared Image Fusion

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 2002, Do and Vetterli proposed contourlet transform which was achieved efficiently by Laplace pyramid decomposition (LP) and directional filter bank (DFB). It provided multi-scale and directional decomposition for images with a small redundancy factor, and therefore it had a unique advantage for small directional contour and line expression [21]. Compared with the wavelet transform algorithm, the contourlet transform could describe the curve "sparser" and make the edge of the obstacle clearer after fusion. The contourlet-based fusion effect is shown in Figure 7.

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



Figure 5. Infrared Image



Figure 6. Visible image



Figure 7. Fusion image

To sharply identify the obstacles in the images, the characteristics of the objects were extracted based on image fusion. 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 characteristics such as the temperature, color, aspect ratio, and rectangularity were chosen for feature extraction from images.

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. Colors were obtained from visible images and expressed in red-green-blue (RGB), and a 3-vector was used to match each color feature.

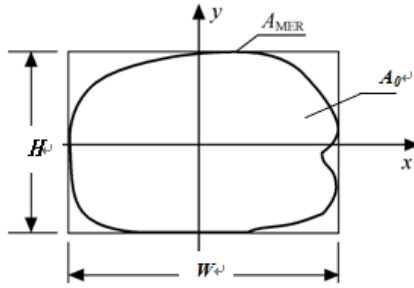


Figure 8. Minimum enclosing rectangle of obstacle

Furthermore, the shape features like the aspect ratio and rectangularity were calculated by segmentation and edge extraction from fusion images with clearer edges of the obstacles. The aspect ratio (A) is expressed as follows:

$$A = \frac{W}{H} \quad (2)$$

where W and H are the width and height of the obstacles, respectively. The aspect ratio describes the obstacle shapes and can distinguish between slender objects and round or square objects. The rectangularity (R) or rectangle fit factor (RFF) ratio is expressed as follows:

$$R = \frac{A_0}{A_{MER}} \quad (3)$$

where A_0 and A_{MER} represent the areas of an obstacle and its minimum enclosing rectangle (MER), respectively. 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.

C. Image ROI Generation by Data Association

The laser and infrared thermal imager are different in representing data. In order to make full use of the information acquired by each sensor, laser data need to be associated with images. This article is to study the static information fusion algorithm, so a simple data association is adopted to get the region of interest [22].

Software settings make laser scanner and infrared thermal imager synchronous to ensure the consistency of the time. Meanwhile, place the two sensors on the same horizontal plane with same pitch angle and calculate the coordinates of the corresponding position to ensure the consistency of the space. Ignore the error caused by the sensors center position deviation, then, data association can be achieved as shown in Figure 9.

In Figure 9, 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 calculation, the result of data association between laser points and thermal image can be shown in figure 10.

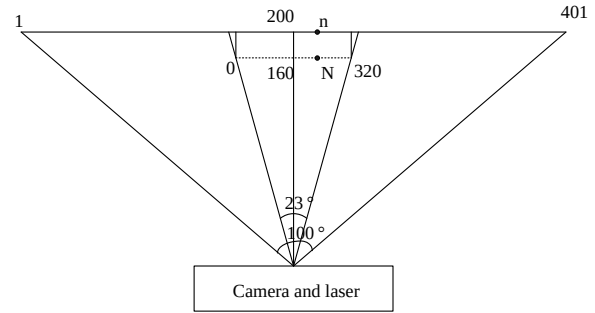


Figure 9. Illustration of the data association



Figure 10. Data association result

After that, objects in laser and image could be associated by formula (4).

$$\begin{cases} |\Delta x(i) - \Delta N(j)| < \varepsilon_1 \\ |x_{1/2}(i) - N_{1/2}(j)| < \varepsilon_2 \end{cases} \quad (4)$$

where

$$\begin{cases} \Delta x(i) = |x_l(i) - x_r(i)| \\ \Delta N(j) = |N_l(j) - N_r(j)| \\ x_{1/2}(i) = \frac{x_l(i) + x_r(i)}{2} \\ N_{1/2}(j) = \frac{N_l(j) + N_r(j)}{2} \end{cases} \quad (5)$$

where $x_l(i)$ and $x_r(i)$ represent the coordinates of the left and right borders of the object i in the image, and $N_l(j)$ and $N_r(j)$ are the coordinates in image corresponding to $n_l(j)$ and $n_r(j)$ which are the coordinates of the left and right borders of the obstacle j in the laser data. If they meet formula (5), it is considered that the two objects i and j are associated. According to practical experience, $\varepsilon_1 = 15$, $\varepsilon_2 = 10$.

D. SVM Classifier for Obstacle Recognition

After the ROI in an image was obtained, an SVM classifier was used for obstacle detection based on various features that were derived from laser points and visible-infrared image.

In 1995, Vapnik first proposed an SVM model built on the basis of the structural risk minimization (SRM) principle. Compared with other machine learning algorithms, SVM has many unique advantages in achieving small sample, nonlinear, and high-dimensional pattern recognition. Its core idea is to convert nonlinear separable problems in low-dimensional space into

linearly-separable problems in high-dimensional space [23-24].

If we assume that two classes in space H can be separated by a hyperplane as follows:

$$w \bullet x + b = 0 \quad (6)$$

where x represents the feature vector, our goal is to calculate the values of w and b to determine the optimal hyperplane which maximizes the margins of the two classes. The optimal values of w and b can be obtained by solving a constrained minimization problem using Lagrange multipliers α_i .

$$f(x) = \text{sgn} \left(\sum_{i=1}^m \alpha_i y_i K(x_i, x) + b \right) \quad (7)$$

In the SVM algorithm, the selection of the SVM kernel function $K(x_i, x)$ is very important because the structure of the feature space is determined by the kernel function. The function selection has a direct impact on classification results. Although many kinds of kernel functions have been proposed, studies have shown that the Gaussian kernel function is preferentially selected if the prior knowledge in practical applications is unknown. The expression is described as follows:

$$K(x, y) = \exp \left(-\frac{\|x - y\|^2}{2\sigma^2} \right) \quad (8)$$

where σ represents the width of the Gaussian radial basis function, and its value is determined by cross-validation. In cross-validation, if there are a set of values σ_i with $i = 1, 2, \dots, n$, the SVM model is trained, and the false classification rate is calculated for each σ_i , σ with the minimum false rate is then selected.

According to the above description, the Gaussian kernel function was adopted to construct a SVM classifier, which performed very well in obstacle classification.

IV. EXPERIMENTAL RESULTS

In the 30 scans, 150 samples consisting of 50 trees, 50 people, and 50 stones were detected. Six features involving the temperature, aspect ratio, rectangularity, and color expressed in RGB were extracted for each sample.

After data collection and feature extraction, an SVM classifier was constructed using the sample data. In order to construct SVM performing the best in this research, the parameter σ of the kernel function is determined by cross-validation with all the sample data. Then, based on the SVM classification principles, 40 samples were selected randomly as the training data and the other 10 as the test data (Table 1).

TABLE I. TRAINING DATA AND TEST DATA

Sample Type	Total Samples	Training Samples	Test Samples
Tree	50	40	10
People	50	40	10
Stone	50	40	10
Total	150	120	30

Finally, the test data was identified and its recognition accuracy rate was validated using the established SVM model. The above process was carried out for 10 times. Table 2 illustrates the obstacle detection results.

TABLE II. OBSTACLE RECOGNITION RESULTS

No.	Tree Recognition	People Recognition	Stone Recognition	Recognition Accuracy Rate
1	10/10	8/10	10/10	93.33%
2	10/10	10/10	7/10	90.00%
3	9/10	10/10	7/10	86.67%
4	9/10	10/10	9/10	93.33%
5	10/10	8/10	10/10	93.33%
6	9/10	7/10	10/10	86.67%
7	9/10	9/10	7/10	83.33%
8	10/10	10/10	10/10	100.00%
9	10/10	10/10	9/10	96.67%
10	9/10	10/10	7/10	90.00%
Mean	9.5/10	9.2/10	8.6/10	91.00%

From Table 2, it is illustrated that the three kinds of obstacles can be identified at a relative high accuracy rate by proposed algorithm, and the correct detection rate of trees and people were higher than that of stones, which might be caused by the feature data having lower discrimination in stone recognition. The obstacles identification result can be shown in figure 11 where different colors of rectangles represent different obstacles.



Figure 11. Obstacles identification result

In general, from the above experimental results, it can be drawn that the obstacle detection method proposed in this paper can achieve obstacle classification and identification in the forest; meanwhile, the method can provide the size, shape, color, position, and other information of obstacles, which facilitates operators to make a right judgment during timber harvest and driving in forest. To sum up, this obstacle detection system has accomplished initial objectives and brought practicable benefits for the future.

V. CONCLUSIONS

In this paper, a obstacle detection algorithm in forest area was proposed based on the fusion of laser data and visible-infrared images. First, the obstacles information was collected by laser a 2D laser scanner and an infrared thermal imager. Then, after images fusion and data association, the features of the objects such as the height, width, shape, temperature, and color could be obtained from the laser points, visible images, and infrared images. Finally, by sample training, an SVM algorithm was used to achieve obstacles recognition. The experimental results

showed that the system accomplished obstacle detection and identification effectively with a mean recognition accuracy rate of 91%, which was practical significance in improving operating efficiency of forest harvester and reducing the risk of causing accident.

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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