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3D LIDAR Point Cloud based Intersection Recognition for Autonomous Driving

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Abstract— **Finding road intersections in advance is crucial for navigation and path planning of moving autonomous vehicles, especially when there is no position or geographic auxiliary information available. In this paper, we investigate the use of a 3D point cloud based solution for intersection and road segment classification in front of an autonomous vehicle. It is based on the analysis of the features from the designed beam model. First, we build a grid map of the point cloud and clear the cells which belong to other vehicles. Then, the proposed beam model is applied with a specified distance in front of autonomous vehicle. A feature set based on the length distribution of the beam is extracted from the current frame and combined with a trained classifier to solve the road-type classification problem, i.e., segment and intersection. In addition, we also make the distinction between $+$-shaped and T-shaped intersections. The results are reported over a series of real-world data. A performance of above 80% correct classification is reported at a real-time classification rate of 5 Hz.**

I. Introduction

When a vehicle is autonomously driving on the road, it not only needs to know where the drivable region is, but also basic road shape and topological relations. Especially if there is an intersection ahead, autonomous vehicles need to be ware of it in advance in order to slow down, to ensure the safety and finally to plan the path.

For the early detection of intersections, one commonly uses Geographic Information System (GIS) in conjunction with position information originating from a Global Position System (GPS) and an Inertial Navigation System (INS). But it remains a difficulty since GIS are often missing, especially in quickly developing countries, or just not updated frequently enough. In addition, GPS is invalid in many places and GIS information does not add benefit without GPS or other localization methods.

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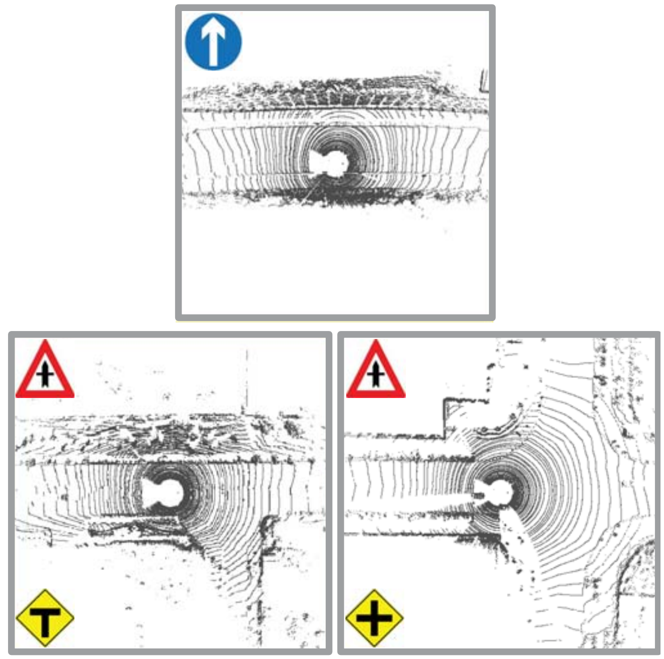

Fig. 1. The goal of intersection recognition is classifying situations ahead of a vehicle as intersection and road segment, and in addition, making a distinction between T-shaped and $+$-shaped intersections.

This paper proposes a real-time intersection detection approach based on 3D point clouds which are acquired by a dense 64-beam scanning LIDAR mounted on the roof of our vehicle. The proposed approach recognizes intersections in front of autonomous vehicle. In addition, it also distinguishes between $+$-shaped and T-shaped intersections. Fig. 1 shows an overview of our work.

II. Related Work

Many existing road intersection detection algorithms are proposed in the field of remote sensing [1]. These methods are based on aerial images which can't be used for autonomous cars. For autonomous driving, video-based methods have been proposed in the past several years [2], [3], [4]. However, poor lighting conditions such as overcasts, overexposure and other interference from moving vehicle and pedestrian make video-based method an extremely difficult and nearly impossible task even if sophisticated image processing techniques are used at the expense of processing speed.

Therefore active sensors are nowadays used widely. Kodagoda *et al.* [5] makes use laser measurements for speedy extraction of two corresponding road edges or curbs using the laser depth measurements and an extended Kalman filter to detect Y-,T- and X-junctions. Wijesoma *et al.* [6] applies a 2D laser scanner co-operated with CCD cameras for road curb tracking. Aycard *et al.* [7] also uses multiple sensors including LIDAR and stereo vision, but it mainly focuses on safety on road intersection including the tasks of moving vehicle and pedestrian perception and risk assessment instead of intersection finding.

Different from the above method, this paper proposes a real-time capable intersection algorithm based on the high-end sensor Velodyne HDL-64ES2 which has a better ability to perceive a wider range of data around. This sensor is more and more popular in intelligent vehicle fields. Our work is somewhat similar to [8]. They use the beam model of range finders from [9] but then apply a distance function versus the angle of each beam to find intersections. Our algorithm improves the beam model and makes a speed related launching point for beam which seams more reasonable for a moving autonomous vehicle. Furthermore, the detection problem is modeled as a classification problem and the machine learning methods can be used to solve it.

Specifically, the proposed method is distinguished from related approaches in the following ways:

- The proposed method models the intersection detection as the classification problem. All method based on machine learning can in principle be used to solve this issue.
- We add width information for each ray of the traditional beam model. The width is a little wider than width of autonomous vehicle; all rays which do not end in an obstacle are more likely to be the drivable region. Based on this, the feature extracted from the beam model are more effective.
- The launching point of beam is an adaptive distance in front of autonomous vehicle instead of a fixed distance. This distance is related to vehicle speed. The faster the vehicle is, the longer distance is. This design goes along with the demands of autonomous driving.

The rest of the paper is organized as follows. In the next section, we introduce beam-based feature construction. Then results from SVM-based classification with proposed features are presented in section IV. Conclusion is given in section V.

III. Beam-based feature construction

This section introduces the construction of a length distribution based on the beam model. First, we build square grid map for each frame of the point cloud; then the cells belonging to other vehicle will be removed from grid map; beam will be launched in adaptive distance in front of the autonomous vehicle, every length of each beam is combined as the feature vector for classification.

A. Data preprocessing

Obstacles mainly includes road curbs, trees, pedestrian and other vehicles. In our method, we want to remain road curbs and wipe off other obstacle from the grid map. Considering that most trees are beyond the road, we just need to remove the vehicles and pedestrians. In this paper, we apply an effective method to detect the vehicle and pedestrian based on external cube generated by adjacent cells in grid map. The basic step is as follows:

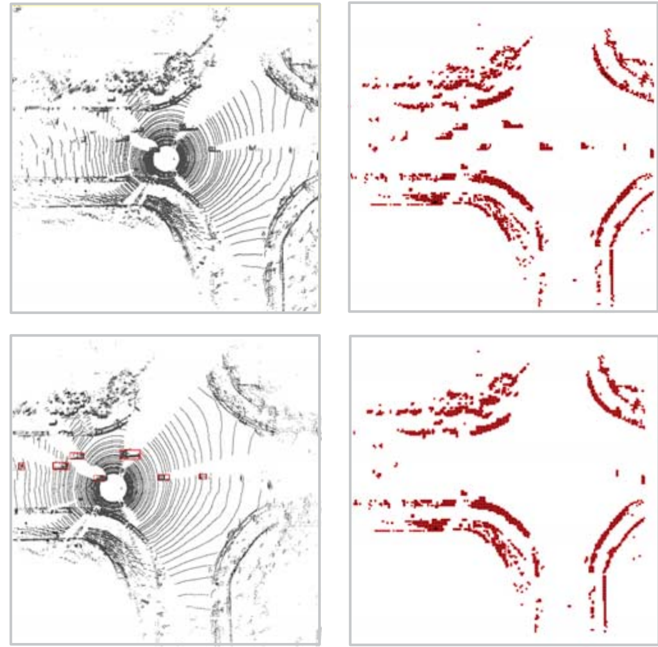

Fig. 2. Step-by-step results of preprocessing: original data; the grid map; vehicle and pedestrian detection and the remaining grid map after removing vehicles and pedestrians.

1) Create a grid map for a frame of data each with quadratic cell size $r \times r$; calculate variance of elevation of the points in corresponding cell.
2) Based on the variance of the elevation we use a threshold on the grid map; if the variance of the elevation is greater than the given threshold, the corresponding entry of the grid is set as 1, otherwise it is set to 0. Then the grid map forms a 2D image which is similar to binary image of the scene in brid-eye view.
3) Traverse all the cells of the grid map. We assemble all the connected cells whose 4-connected regions are all 1 as a connected region. Afterwards, we rebuild these connected regions to surround a cube.
4) Using the length and high of the cube, we detect the vehicles and pedestrians.
5) Clear the cells which is belong to vehicle and pedestrian, the remaining grid map will be used for intersection recognition.

Figure 2 shows the procedure of the preprocess, along the direction of the arrows, there are original data, the grid map, vehicle and pedestrian detection and the remaining grid map after clearing vehicles and pedestrians.

1) Beam model and feature construction: A probabilistic beam model is discussed in detail in [10]. It is an approximate physical model of range finders and widely used in mobile robotics.

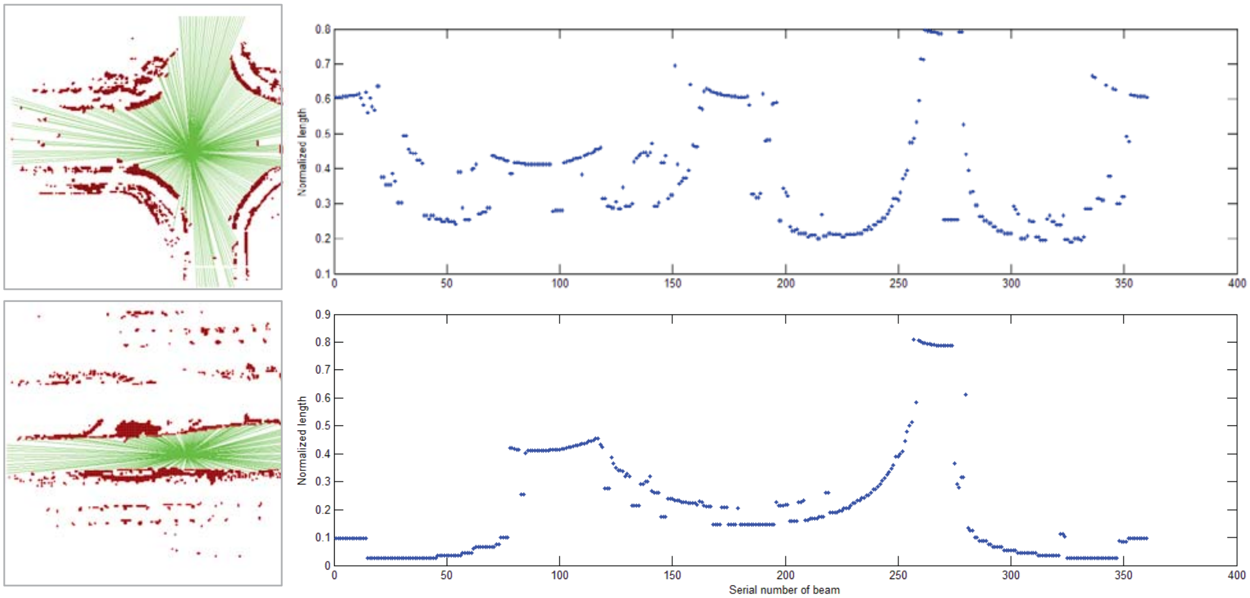

Fig. 4. Examples of beams in intersection and road segment, and corresponding histogram of length distribution. The top one is the intersection and the bottom one is the road segment.

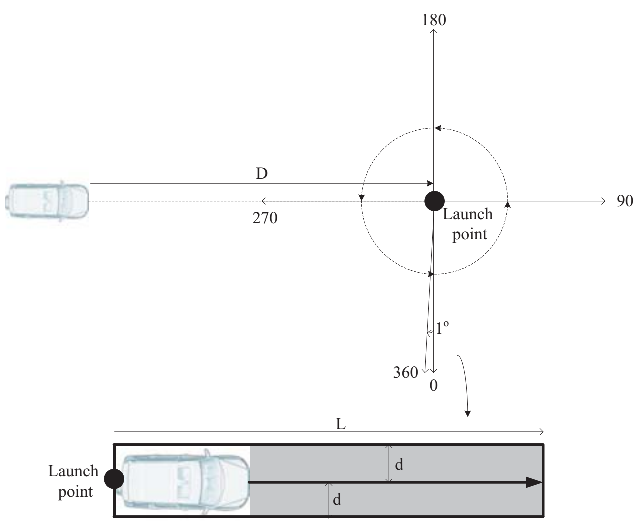

Fig. 3. Beam model. 360 Numbered beams emitted from an adaptive launching point, each beam has a width information which is little wider than the autonomous vehicle.

Our beam model is a sequence of beams with same launching point which is within the adaptive distance in front of the autonomous vehicle, the distance is related to the speed of the autonomous vehicle with the unit in meter per second. See Fig 3, the amount of beams of our model is 360 with a 1° angle of two adjacent beams. Different from the beam model in [10], we allocate each beam a width that is a little greater than the width of the autonomous vehicle and enumerate all the beams from 0 to 359.

Then we launch our beam model in front of the vehicle with special distance which depends on the vehicle speed (see Eq. (1)), D is the distance from between the autonomous vehicle and the launching point, v is the speed of the autonomous vehicle. The higher the speed is, the longer is the distance and the slower speed is, the shorter is the distance. This strategy is more reasonable than using a fixed distance such as proposed in [8]. All the beams scan linearly from the launch point. There it will be cut off when the beam hits an obstacle grid cell. If the beam is not blocked, its length is limited to a constant L. For intersections and road segments, the distribution of the length of each beam is different. See Fig 4, the normalized length histogram of the beam in intersections and road segments is different. For road segments, there are two local peaks but for $+$-shaped intersections there are four local peaks, Based on this, we choose the normalized lengths of all the 360 beams in one frame as the a feature, so the feature is just a 360-D vector.

$$D = 5 + v * t; \quad (1)$$

Where $t = 1s$ in this paper.

2) Feature classification: The problem of feature classification over these features descriptor is then formulated as supervised machine learning problem with labeled classes for the two-class classification problem. Due to the better ability for learning from a small sample set, we apply a Support Vector Machine (SVM) [11] as our classifier. We consider the normalized length of all the 360 beams as 360 features and uses the SVM for an analysis and learning. The resulting classifier is used to classify other unknown road scenarios.

IV. EXPERIMENTS AND RESULTS

To verify the effectiveness of the proposed method, we present experiments of applying our algorithm to two kinds of different data sets; Data set 1 contains 264 frames of $+$-shaped intersections, 136 frames of T-shaped intersections and 400 frames of road segments without intersections; all

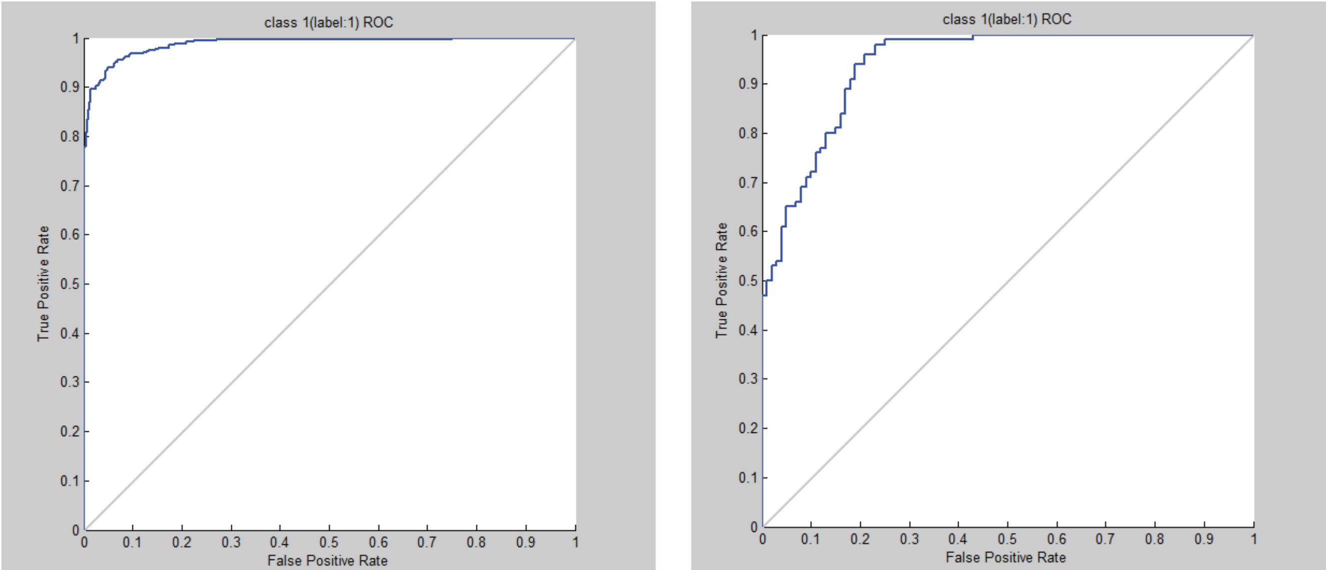

Fig. 5. ROC curves of classification on two test data sets, from left to right, are ROC curves of classification on data set 1 and test data set 2.

the road conditions in data set 1 are relatively good with less interference from other vehicles or pedestrians. In addition, we also prepared a second data set with challenging road conditions including many other vehicles and pedestrians to evaluate the robustness of proposed algorithm. Data set 2 contains 44 frames of $+$-intersections, 56 frames of T-intersection and 100 frames of intersection-free road segments.

All of the data are acquired by the Velodyne scanner which is mounted on the top of our intelligent vehicle in Wuhan and Erdos, China. Figure 6 is the intelligent vehicle named SmartV, developed by Wuhan University. The vehicle velocity is within or at the national legal speed limit for the class of roads being considered. The Velodyne HDL-64ES2 is a dense 64-beam scanning LIDAR that provides 360-degree coverage at 10 Hz, generating just over 1 million 3D points with associated infrared remittance values per second.

Fig. 6. The intelligent vehicle of Wuhan University:SmartV, the sensor labeled by red rectangular box is Velodyne scanner.

A. Intersection and road segment classification

The set of manually labeled examples used for training SVM classifier is made of 1300 frames of point clouds 150 frames of $+$-shaped intersections, 150 frames of T-shaped intersections and 1000 frames of road segments, all the intersections are labeled as positive examples. The performance on test data sets by trained classifier is shown in Fig. 7 and Table I. We use the true positive rate (TPR), the true negative rate (TNR), the total accuracy, the receiver operating characteristic curve (ROC) and the area under curve (AUC) to evaluate classification results. The TPR, TNR and accuracy are all above 99% and the ROC curve is approximation to the top left corner. For test data 1, TPR is 91.25%, TNR is 96%, the total accuracy is above 93%, AUC is about 0.98, this result is preferred. For the challenging data set, the TPR, TNR and total accuracy is all falling below 85%, but above 80%. That suggests, more disturbances also bring higher difficulty. Some more effective preprocessing will be considered in future work.

B. T-shaped and $+$-shaped intersection classification

After detecting the intersections, we recognize the type of this intersection as T-shaped or $+$-shaped. The training data for this task is extracted from previous described training data, 150 frames of T-shaped intersections are labeled positive examples, and 150 $+$-shaped are labeled as negative examples. The performance of classifier in shown in table II. For test data, the accuracy is below 90% but above 80%. We can see that the accuracy of T- and $+$-shaped classification is lower than the accuracy of the classification of intersection and road segment. We will improve this accuracy by designing better features and increase the number of training data. In general, the results are acceptable.

TABLE I

SVM PERFORMANCE ON INTERSECTION AND ROAD SEGMENT CLASSIFICATION

	TPR	TNR	Accuracy	AUC
Test Data 1	91.25%	96%	93.625%	0.987
Test Data 2	81%	84%	82.5%	0.938

TABLE II

SVM PERFORMANCE T-SHAPED AND $+$-SHAPED INTERSECTION CLASSIFICATION

	TPR	TNR	Accuracy
Test Data 1	93.382%	80.681%	85%
Test Data 2	85.714%	79.545%	83%

Figure 7 shows some examples of successful classification for road environments. As presented, the approach described here operates in near real time at approximately 5 Hz on an PC with Intel(R) Core(TM)2 Duo CPU at 2.3Gz.

V. CONCLUSION

This paper proposes a LIDAR-based real-time capable intersection recognition algorithm for autonomous driving. First, we build a grid map from point cloud data and remove the vehicle from the map. Then a beam model is launched and the launch point is within an adaptive distance in front of autonomous vehicle. Finally, we exploit a trained classifier based on a SVM. We classify the current road shape as intersection and road segment. In addition, we recognize T-shaped intersection and $+$-shaped intersection. Different complexity of test data are experimented to demonstrate the effectiveness and robustness of the proposed method. In the future work, we will in addition to improve the accuracy of intersection recognition, detect more attributes of intersection such as the direction and width.

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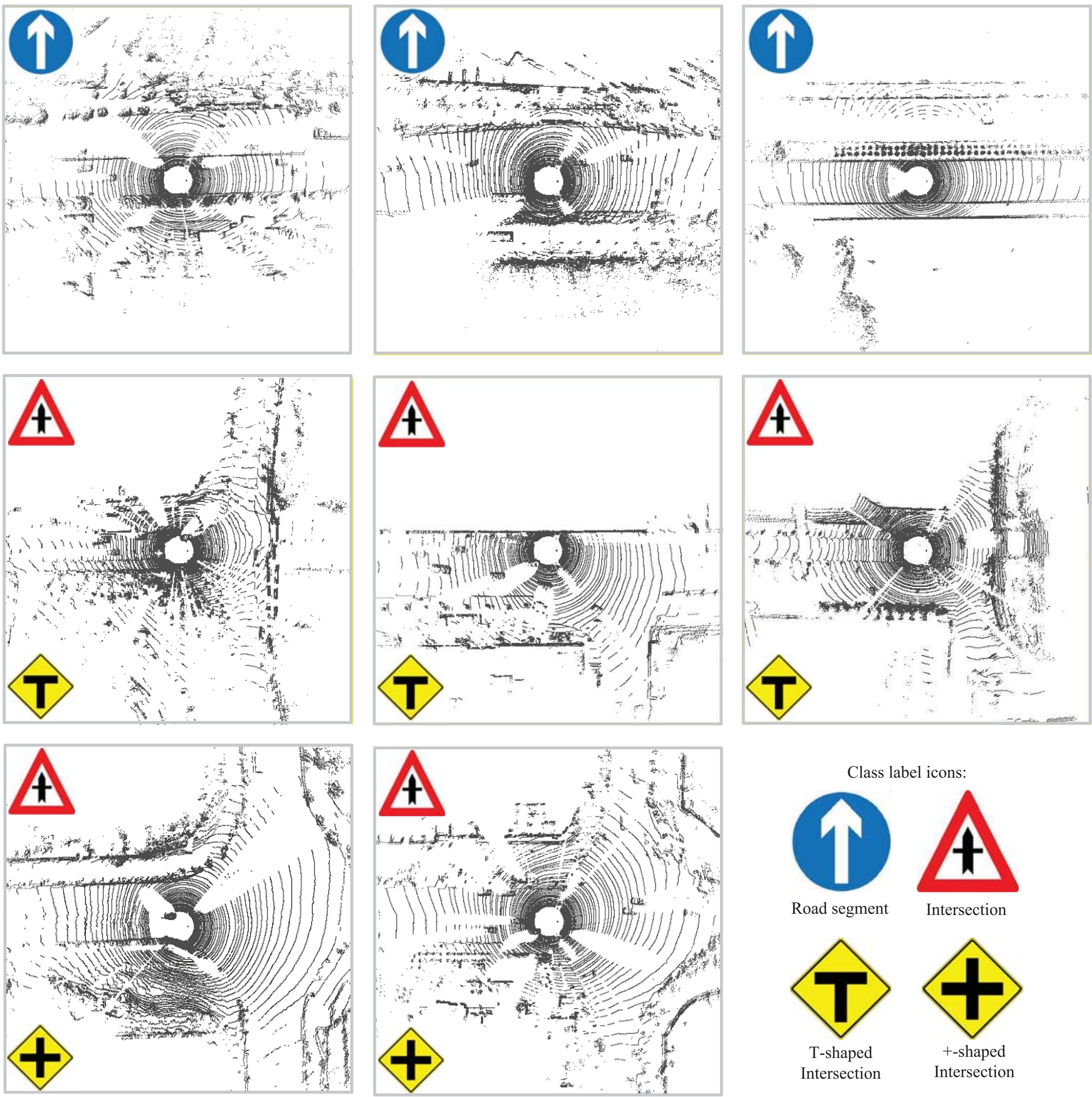

Fig. 7. Examples of successful classification. The first row are examples of road segments; the second row are examples of T-shaped intersections; the last row are examples of "+"-shaped intersections.