Safe and Reliable Movement of Fast LiDAR-based Self-driving Vehicle

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Abstract: Classification of objects is an important technique for autonomous ground vehicles to identify a surrounding environment and execute safe path planning. In this paper, a method based on horizontal segmentation is proposed to detect cone-shaped objects in vehicle's vicinity using a LiDAR sensor. A captured point cloud is divided into five layers based on height information, and the division of detected objects into two groups, cones and others, has been made using classifiers available in MATLAB toolboxes. To separate the classified conical objects into four types used to mark the route, an algorithm for their recognition was developed and used. The proposed solution, verified by navigation experiments in real conditions using an unmanned racing car, has gave good results, i.e., a high rate of cone-shaped objects classification, a short processing time and a low computational load. The performed tests have allowed also to diagnose the causes of incorrect classification of objects. Thus, the experimental results indicated that the approach presented in this work can be used in real time for autonomous, collision-free driving along marked routes.

Keywords: wheeled ground vehicle, autonomous driving, object classification, LiDAR

1. Introduction

An unmanned ground vehicle (UGV) can be thought of as a robotic platform that actively interacts with its environment. Accurate surrounding perception and precise localization are key requirements for its reliable navigation and safe driving. These two tasks need the vehicle to be equipped with the following three main components, i.e., a set of sensors to perceive the external environment; a computing device to process data in real time in order to analyze the situation; actuators to carry out the required control actions.

Nowadays, light detection and ranging (LiDAR) sensors have been employed increasingly for observation of complex environment due to their advantages like high scanning accuracy, long-distance measurement, high resolution and stability. The LiDAR provides information in the form of a point cloud that can be used to identify objects around the vehicle to ensure collision-free riding. In the case of the fast-moving wheeled vehicle, this task requires the use a high-speed computing device, effective data processing algorithms and efficient use of memory.

In this paper, we propose a two-stage framework to detect and classify cone-shaped objects for the purposes of safe vehicle autonomous driving along a designated urban route in the shortest possible time. First, shape information is extracted from LiDAR data using classifiers available in the MATLAB toolboxes. Then, the obtained dataset is divided into four types of objects using a developed and implemented algorithm. Correct recognition of the cones makes it possible to determine the vehicle's position in space, which is the basis for the path planning task.

The remainder of this paper is organized as follows. Section 2 documents the related works. Section 3 presents the mobile vehicle and external environment used for experimental trials. Section 4 describes a procedure for classifying objects from LiDAR data based on layered feature extraction and evaluates the effectiveness of the proposed approach. Section 5 presents a developed algorithm for the detection of cone-shaped objects and results of experiments conducted in real conditions. Conclusions are given in Section 6.

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2. Related works

In In recent decades, autonomous vehicles with the perception of the environment in terms of intelligent urban traffic have been extensively studied [1–8]. In this field, effective object detection methods are sought in order to create an environmental model around the vehicle and execute path planning. To achieve a high level of perception system, sensors such as cameras, radars, lasers or LiDARs are installed in vehicles [9–18].

Currently, the last ones are used more and more often in unmanned driving [19–24]. Therefore, a lot of works are conducted for processing LiDAR data, especially in the area of autonomous navigation and movement [25–28]. Traditional detection methods from obtained 3D point clouds primarily analyze and extract features, such as geometric or shape attributes, and then classify objects by trained specific classifiers [29, 30].

The problem of object detection consists of two main topics, namely: object extraction and classification. Therefore, the point clouds are first pre-segmented, and potential objects are divided into clusters. Then a set of global features is defined and the objects are identified as a whole [31].

This work attempts to meet challenges associated with object classification from LiDAR data by means of layered feature extraction.

The concept of slicing a point cloud cluster to extract features is not new, but it is usually described as part of the system architecture rather than the independent process. An interesting review of the use of vertical point cloud segmentation to identify geometrical features of objects was presented by Kyriazis and Fudos in [32]. Spinello *et al.* [33] divided point clouds into several layers based on height information. Feature extraction and classifier training were then performed for each layer. They claimed to achieve overall accuracy more than 90 %. Kim *et al.* [34] used layer features to classify people and estimate their poses. The interesting approaches to using of layer features, based on the curvature of the object, were presented by Tombari *et al.* in [35]. Luo and Yan-min [36] used horizontal segmentation, plane projection, and shape fitting for rapid extraction and reconstruction of building pillars from the scene. Their approach was extended by Pu *et al.* [37] with percentile-based pole recognition for detecting objects such street lamps. The results showed that focusing on number of layers can have a significant impact on computational efficiency of the classification method.

Although a lot of works have been done on the layered feature extraction technique classification of objects using LiDAR data, there are still some problems that require further in-depth research. One of them is how to reduce the computational load of data processing to obtain the goal of real-time operation. During autonomous driving, nearly a hundred objects must be classified in each LiDAR frame with a range of up to 50 m, therefore low processing time is a crucial parameter, especially in the case of a fast-moving vehicle. In connection with the above the authors present a solution in this field which can facilitate the detection of cone-shaped objects. The key idea of the presented method is to determine a minimum number of layers for given objects, sufficient to classify them with an assumed accuracy. It allows to speed up time-consuming process of LiDAR data processing and reduces the size of stored data.

3. Autonomous vehicle and external environment description

The UGV shown in Figure 1, called LEM, was designed and built to meet requirements of the AGH University of Science and Technology Racing Driverless Vehicle Team. The vehicle is an example of a racing car capable of driving in autonomous mode. It is the four-wheeled vehicle that can reach speeds of up to 120 km/h. The construction has the following parameters: length – 2.8 m, height – 1.2 m, width – 1.4 m and mass about 250 kg.

Fig. 1. A view of the LEM unmanned ground vehicle
Rys. 1. Bezzałogowy pojazd naziemny LEM

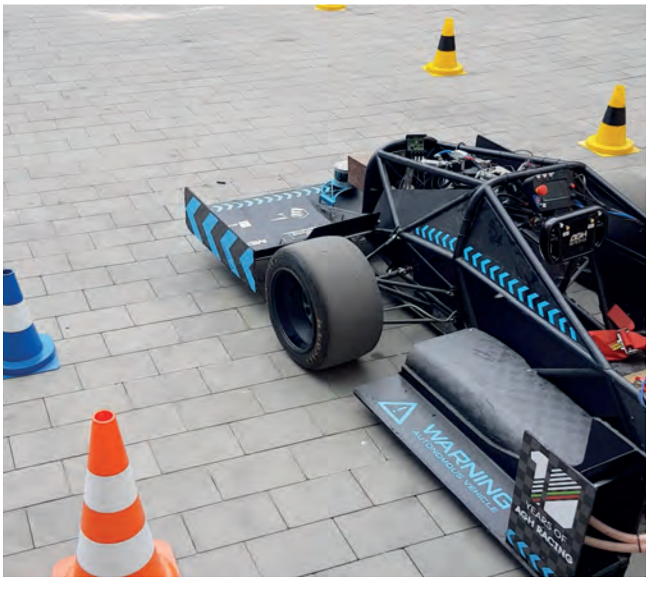

Fig. 2. The LEM vehicle among cones during a test
Rys. 2. Pojazd LEM między stożkami drogowymi w czasie testu

A task of the vehicle was to drive as quickly as possible along a 1,000-meter route, determined according to the following rules:
- a left boundary of the track was marked with small blue cones,
- a right boundary of the track was marked with small yellow cones,
- a maximum distance between two cones in the direction of travel was 5 m,
- a maximum transverse distance between two cones was 5 m,
- big orange cones were placed before and behind lines marking the start and finish.

A view of the LEM vehicle among cones during the field experiment is shown in Figure 2.

A safety driving needs the vehicle to be able to detect and recognize objects in the outdoor environment. For these tasks the vehicle is equipped with the Velodyne VLP-16 LiDAR system mounted on the front spoiler (see Figure 1). This on-board perception sensor was chosen because of its advanced technical parameters, in particular reliability, power efficiency, and surround view, which makes it ideal for affordable low-speed autonomy. The LiDAR has 16 channels, measurement range up to 170 meters, accuracy ±30 mm. The key parameters of VLP-16 can be found in the reference [38].

The LiDAR is connected to the on-board NVIDIA Jetson TX2 data processing unit via the USB 3.0 interface. The unit is equipped with a Quad-core 2.0 GHz 64-bit ARMv8 A57, a dual-core 2.0 GHz ARMv8 Denver, a 256 CUDA core 1.3 MHz NVIDIA Pascal and 8 GB memory [39]. It runs under the control of the Linux operating systems, and provides greater than 1TFLOPS of FP16 compute performance.

4. Classification stage and data processing

Point cloud processing tools included in the Computer Vision Toolbox and Statistics and Machine Learning Toolbox were used for calculations, available via executable files generated in the MATLAB environment and coded in C++.

The objects were detected from the LiDAR data using the Euclidean clustering, under assumption that the point clouds were normalized between values 0 and 1 and divided into five layers. Examples of features extracted from the layers are depicted in Figure 3. Then the isolated objects were split into two classes, i.e., cones and others (non-cones).

Figure 4 shows the example of virtual image of the route and its immediate surroundings, obtained on the basis of processed LiDAR data (a single frame), showing detected the cones and not cones on a 50-meter long section.

An efficiency of the feature extraction procedure for different number of layers was analyzed by changing parameters in appropriate scripts. The initial number of layers was equal to 1 to set up a baseline for measuring feature extraction performance. For each layer the following parameters were calculated:
— percent of cluster points belonging to the layer;
— standard deviation for XY coordinates;
— average distance from cluster center in XY coordinates.

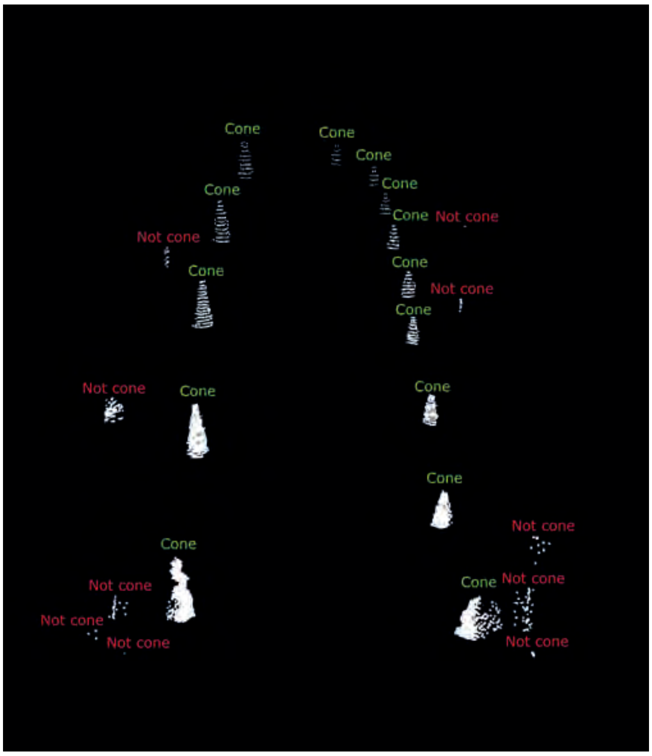

Fig. 4. Visualization of results of classification procedure for a single LiDAR frame
Rys. 4. Wizualizacja wyników klasyfikacji dla pojedynczej ramki systemu LiDAR

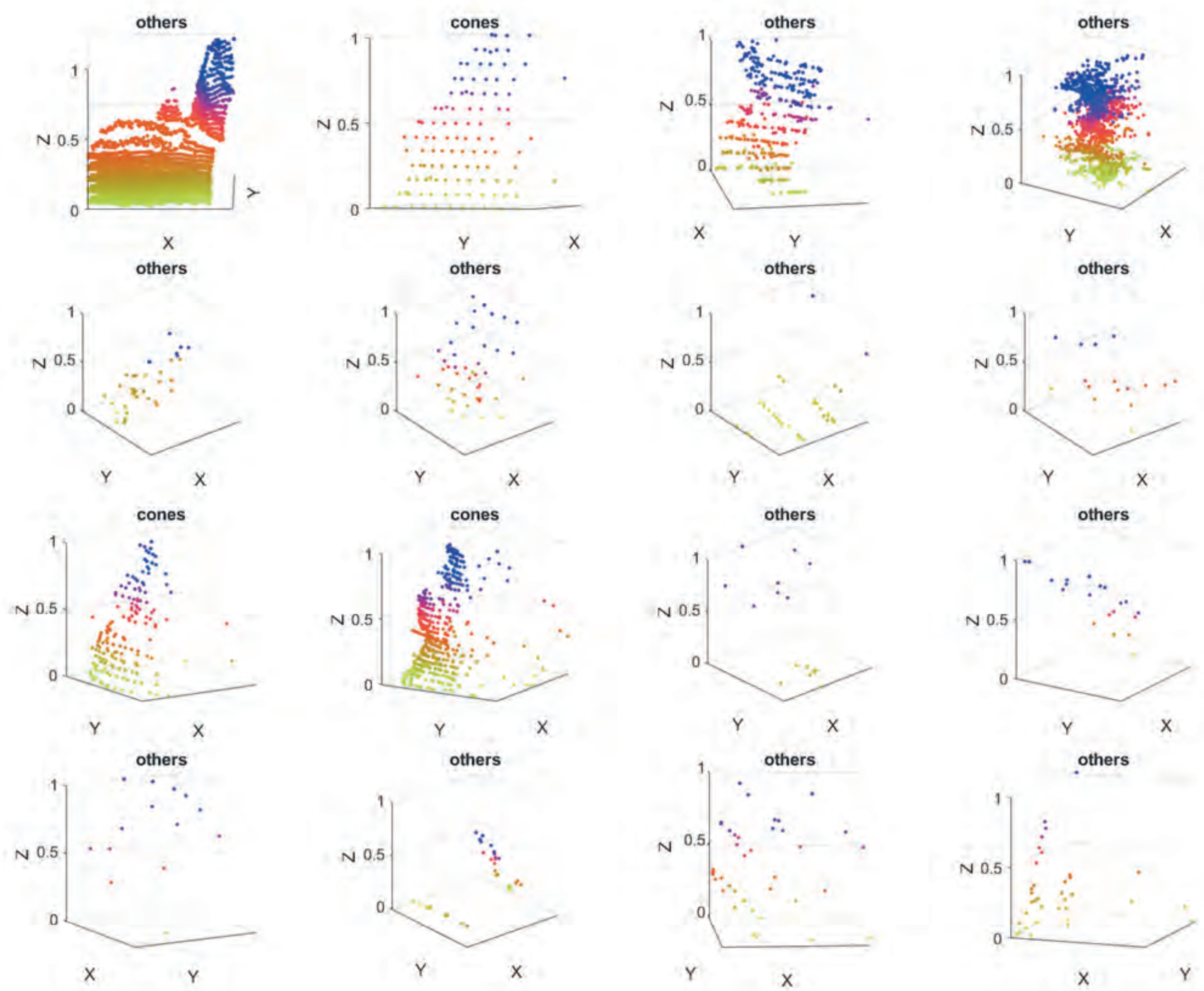

Fig. 3. Examples of features extracted from vertical layers
Rys. 3. Przykłady cech wyodrębnionych z warstw pionowych

The data set, consisting of a total of 1271 objects, was randomly divided into three subsets: training, validation, and testing in proportions of 2:1:1, respectively. The training and validation sets were used by the Classification Learner app to train the classifiers. Then, the testing set was used to evaluate the performance of the trained classifiers. The average accuracy and the true positive rate (TPR) for both classes of objects and three most effective classifiers are presented in Table 1 and Figure 5.

From the results presented in Table 1 and Figure 5, the following conclusions can be drawn:
- the true positive rate (TPR) values for cones and others objects are almost on the same level for each layer considered;
- starting with a certain number of layers, the effectiveness of the classifiers does not improve significantly as the number of layers increases.

As mentioned in Section 3, the task of the AGV was to cover the route in the shortest possible time. Therefore, low processing time per object was the basis for safe autonomous driving of the regarded racing car. The last conclusion indicates that the appropriate selection of the number of layers can be an effective way to speed up the processing time of captured LiDAR data.

5. Cone type recognition algorithm

The input to the algorithm is a part of the LiDAR data representing the vehicle's surrounding, consisting only of objects belonging to the cones class. A task of the algorithm is to divide this dataset into four types: big orange cones, blue cones, yellow cones and unknown (cones).

A block diagram of the algorithm is depicted in Figure 6. The first part calculates basic statistical data about the objects, i.e., cones: number of points, average intensity, standard deviation. In the next step, the point cloud is sorted according to coordinates in vertical axis (Z coordinate), using the insertion sort. This kind of solution was chosen because it works quickly for small number of elements, is simple to implement and has a low memory consumption. After sorting the algorithm extracts the height of the point cloud by subtracting the minimum of Z from the maximum of Z. Then, the algorithm checks whether the cone is the big orange cone by asses-

Tab. 1. Results for different numbers of layers for the best three classifiers
Tab. 1. Wyniki uzyskane dla różnych liczb warstw z użyciem trzech najlepszych klasyfikatorów

Number of layers	Best models accuracy [%]	TPR cones [%]	TPR others [%]
1	69.1	67.0	70.1
	68.1	68.9	67.8
	68.1	62.1	71.0
2	92.7	86.3	95.5
	92.1	96.8	90.1
	92.1	94.7	91.0
3	94.3	92.9	95.0
	94.0	93.9	94.1
	93.7	92.9	94.1
4	93.4	91.8	94.1
	92.7	92.9	92.7
	92.4	92.9	92.2
5	96.5	93.8	97.7
	96.2	95.9	96.4
	95.9	95,0	94.5

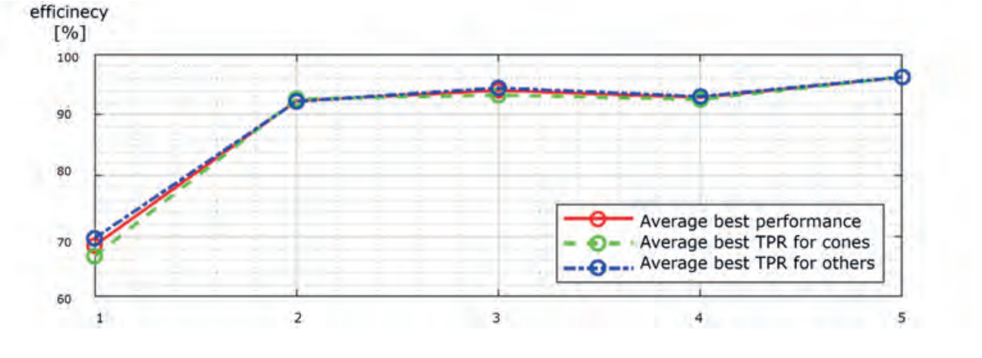

Fig. 5. Efficiency of three best classifiers against number of layers
Rys. 5. Efektywność trzech najlepszych klasyfikatorów w zależności od liczby warstw

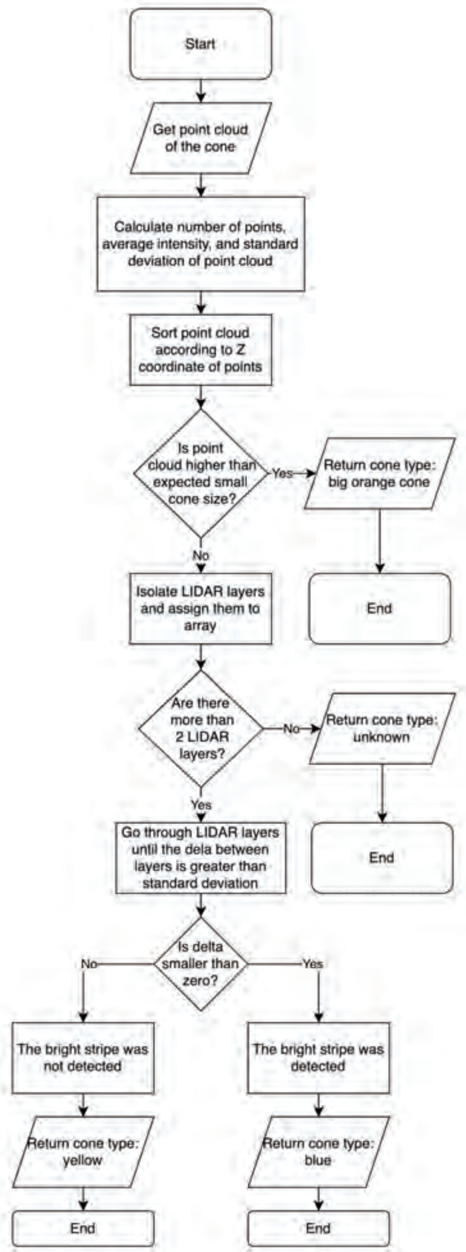

Fig. 6. Block diagram of cone type recognition algorithm

Rys. 6. Schemat blokowy algorytmu rozpoznawania typu stożka

sing its size. It saves time and computational resources as the algorithm can accomplish it without checking the color layers. The next step is the isolation of layers. The algorithm goes through points, summing the intensities of points, and counts their number. If the difference between Z coordinates, (called delta), is higher than threshold it saves the number of layer points in one array and the layer average intensity in another array. If the number of layers is less than 3 it is assumed that the point cloud is too small to recognize the cone type correctly, hence the algorithm returns the cone type as unknown.

The final part of the algorithm checks whether the cone has a bright stripe. It's done by going through the LiDAR layers, starting from the bottom. If the delta between layers is greater than standard deviation of the cone intensity, it is assumed that the border between body and stripe was reached. The standard deviation was used as a threshold due to two reasons. Firstly, the further the cone is from the LiDAR system, the smaller the dynamic range of the points intensities. Therefore, the standard deviation is a good indicator of this range. Secondly, it was tested in real conditions and for different parameters used to differentiate between the layers, the standard deviation turned out to be the most effective. Then, after checking whether

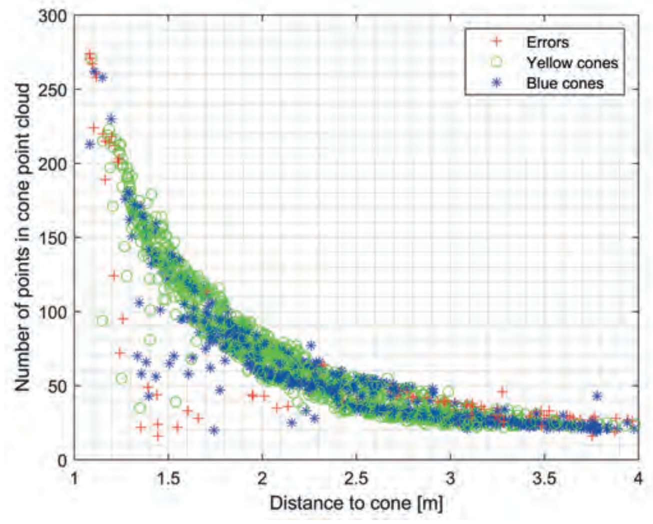

Fig. 7. Correlation plot between the distance of the cone and the number of points

Rys. 7. Wykres korelacji pomiędzy odległością stożka a liczbą punktów

it has gone from bright to dark or vice versa, it assigns a label (a Boolean value) to the cone indicating whether it has the bright stripe or not. Thus, the cone is treated as either blue or yellow, depending on whether it has a bright stripe, or not. The algorithm was implemented in MATLAB and tested on the dataset containing 1910 items, all represented by five layers. Results of cones recognition are shown in Figure 7. The total number of errors was 116 and the overall efficiency of the algorithm was approximately 93 %. It can be noticed that the considered objects, i.e., the cones, are axisymmetric. Hence, it does not matter from which side the LiDAR observes the cones. The captured point cloud is more or less the same, and even if the distance from the sensor increases, the shape and proportions are retained. Nevertheless, for the classification based on statistical methods and not using artificial intelligence requiring high computer power, it is a quite good result, confirming effectiveness of proposed approach.

Detailed analysis of the results presented in Figure 7 also allows conclusions to be drawn about probable sources of errors. Most of the errors happen below the 64 and above 190 points in the cloud. These are cones in which the number of points is too small and may result of faulty clustering. This applies in particular to cones for which the distance to the sensor is less than 1.25 meters and then they are usually not fully illuminated by the laser beams. The above means that correct identification of the cone depends on the number of points in the point cloud and the distance between the object and the LiDAR sensor.

The research was carried out on a dataset consisting of the above-described items represented by three and four layers. Obtained results were like those presented in Figure 7 and suggest that focusing on number of layers can have a significant impact on the computational efficiency of the classification process. The fewer layers are analyzed the better the classifier performance.

7. Conclusions

This paper presents a method for object classification using 3D LiDAR data enabling safe operation and reliable driving in autonomous mode of the UGV. For this task, the work was focused on classification and recognition of two objects occurring in road environments: cones and others.

Firstly, the collected environmental data were processed using horizontal segmentation as the features extraction method. The object cluster was split into five number of horizontal layers. The overall accuracy of both regarded objects achieved about 95 %. Taking into account the accuracy of the classification process, it was noticed that starting from a certain number of layers, the accuracy level did not improve significantly as the number of layers considered increases. Therefore, considering the fact that computing the features of each layer requires time and resources, specifying the sufficient number of layers could speed up the processing time of the classification procedures.

Secondly, in order to determine the vehicle's position in space and a safe route, the recognition algorithm was introduced, dividing the detected cone-shaped objects into four types. Its overall accuracy was 93.3 %. Errors in the recognition results were also diagnosis. The worked out classification algorithm is characterized by a relatively low computational load, making it suitable for use in real-time applications in autonomous vehicles equipped with limited power computing units.

The proposed approach was tested in a real outdoor environment with the LEM AGV as an autonomous mobile platform. The obtained results showed that the classification process met the expected requirements, safe and reliable vehicle movement was ensured, and navigation objectives were achieved. The experiences showed that the distance of the cone from the sensor has a big impact on the accuracy of the classification. Therefore, in the future, it is planned to divide the process into two stages: short distance and other. This should improve the final classification quality.

Further work will focus on extending the functionality of the classification procedure so that it can be successfully applied to other classes of road objects.

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Bezpieczna i niezawodna jazda szybkiego pojazdu autonomicznego z użyciem systemu LiDAR

Streszczenie: Klasyfikacja obiektów jest ważną technologią dla lądowych pojazdów autonomicznych pozwalającą na identyfikację otaczającego środowiska i zaplanowanie bezpiecznej trasy przejazdu. W artykule zaproponowano metodę klasyfikacji opartą na segmentacji poziomej do wykrywania obiektów w kształcie stożka drogowego w pobliżu pojazdu za pomocą sensora LiDAR. Przechwycona chmura punktów jest dzielona na pięć warstw na podstawie informacji o wysokości, a podziału wykrytych obiektów na dwie grupy, stożki i inne, dokonano z wykorzystaniem klasyfikatorów dostępnych w przybornikach środowiska obliczeniowego MATLAB. Do rozdzielenia sklasyfikowanych obiektów stożkowych na cztery typy, wykorzystywane do oznakowania trasy przejazdu, opracowano i zastosowano algorytm ich rozpoznawania. Zaproponowane metoda, zweryfikowana eksperymentami nawigacyjnymi w warunkach rzeczywistych z wykorzystaniem bezzałogowego samochodu wyścigowego, dała zadowalające wyniki, tj. wysoki poziom klasyfikacji obiektów w kształcie stożka, krótki czas przetwarzania i niską złożoność obliczeniową. Przeprowadzone testy pozwoliły także na zdiagnozowanie przyczyn nieprawidłowej klasyfikacji obiektów stożkopodobnych. Wyniki eksperymentów wykazały, że przedstawione w artykule rozwiązanie może być wykorzystane w czasie rzeczywistym do autonomicznej, bezkolizyjnej jazdy po oznaczonych trasach.

Słowa kluczowe: kołowy pojazd lądowy, jazda autonomiczna, klasyfikacja obiektów, LiDAR

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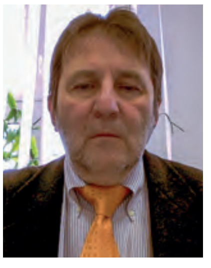

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