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Development of a perception system for railway shunting

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Abstract. In this paper, a perception system for shunting operations is presented making use of a LiDAR, camera and a smart edge computer. Railway relevant obstacle detection and classification are approached and braking behaviour of freight trains are investigated.

1 Introduction

In shunting yards, trains are driven on sight. That causes shunting operations being carried out by two workers: one in the locomotive and one at the end of the train in order to allow driving in both directions. However, standing on the wagon is quite uncomfortable and dangerous. Therefore, the idea is to establish perception systems monitoring the track in order to allow shunting operations carried out only by the locomotive driver in a secure environment and also to enhance operational safety by using new technologies.

Driving backwards with a car using the rear-view camera is already experienced as a challenge due to the limited field of view. Driving a 700 m train from the locomotive, deprived of peripheral vision and other sensory information is expected to be felt even worse by the driver. For this reason, such system must be enhanced with artificial intelligence and augmented reality in order to make the driver being confident and having trust in the system while driving.

In the rail sector, there do not exist any ready to use systems yet. In the automotive sector, there are perception systems already in use, but there is an important difference: automotive vehicles have to monitor the whole space where they can potentially drive. If there are any obstacles coming close to the vehicle, it has to slow down or even stop. On the other hand, trains can only follow along the tracks and as long as the loading gauge is free of obstacles, trains do not have to stop, although an obstacle is close to the track. Therefore, the task is to identify and monitor the loading gauge, especially for longer distances than in the automotive sector since braking distances of trains are much longer.

2 Related work

Various teams are conducting research in this field. Ristic-Durrant et al. presented a concept of a multi-sensory on-board system for obstacle detection [1]. The prototype basically consists of stereo and thermal cameras, a night vision sensor as well as a laser scanner. It is planned to implement a “sensor fusion system for mid (up to 200 m) and long range (up to 1000 m) obstacle detection, which is independent of light and weather conditions” [1].

Johanna Gleichauf et al. [2] on the other hand presented a sensor fusion concept that combines data of laser scanner, thermal and RGB cameras. The obstacle avoiding system’s results are then sent to a control unit on the locomotive in order to allow locomotives shunting autonomously, especially when approaching waggons during shunting.

Both presented systems are permanently mounted to the locomotive whereas the proposed system is portable and mountable to any wagon. In this way, the job of the second worker can be saved and not the one in the locomotive.

3 Method / Approach

The approach presented in this paper bases on sensor box attached to the end of the train equipped with a camera, a mid range LiDAR (Light Detection and Ranging) (up to 200 m) and a smart edge computer in order to monitor the track as shown in Figure 1.

The LiDAR is used to verify that the track is free of obstacles. The output of the LiDAR is a 3D point cloud that represents the environment given in Cartesian coordinates. When rejecting all points that are outside the loading gauge, there should be no points left. If this does not apply, these points can be understood as obstacles and the distance to the obstacle can be extracted. In addition, a k-means clustering algorithm is used in order to group points of detected obstacles. In this way, for every found obstacle/cluster a measured distance can be assigned. The point cloud is processed with the C++ point cloud library [3].

Figure 1. Sensor box attached to the train monitoring the track.

The camera is used to identify and classify objects such as persons, wagons, signals and the track. For the identification and classification of pedestrians in the first step, the spatio-temporal convolutional neural network named PedNet has been tested [4]. Besides that, a list of all shunting relevant signals has been compiled in order to manually label recorded data for neuronal network (NN) training purposes. Wagons, persons and tracks are labelled as well. The label process is still ongoing.

In addition, braking curves have been investigated so that the braking distance of the train can be calculated. This allows assessing whether an object inside the loading gauge is in danger or whether the train will stop early enough.

Figure 2 shows a concept of how a human machine interface inside the locomotive could look like in order to assist the driver. It includes a video live stream overlaid with highlights on signals, a person, a waggon as well as the tracks and the train's braking distance (red colour).

Figure 2. Augmented Reality in camera live stream highlighting persons, wagons, signals and the driveway including the braking distance.

4 Results

With the use of the Robosense RS32 LiDAR obstacles in 60 m distance on straight tracks can be found, but future tests are expected to prove longer distances due to adjustments in the clustering algorithm. Figure 3 illustrates the initial situation (raw point cloud) on the left and the result (filtered and clustered point cloud with distance to obstacle) on the right.

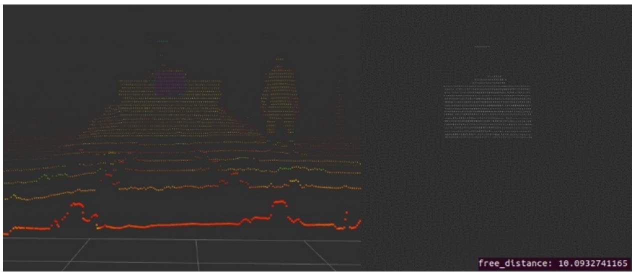

Figure 3. Left: Point cloud showing the tracks, a bumper with a signal on it and a person standing next to the bumper. Right: Filtered point cloud with points only in the loading gauge. Free distance in meters is calculated.

The PedNet aims at pedestrian segmentation, but it has been found out in the conducted experiments, that the algorithm struggles with identifying people wearing reflective vests. This is critical since these are mandatory in railyards due to safety reasons.

The calculated braking curves show that in worst case scenarios (downhill gradient of 2,5 ‰, no airbrake, wagons just below changeover mass) loaded freight trains have braking distances up to 534 m whereas in best case scenarios (downhill gradient of 0 ‰, airbrake, brake mode G, wagons just above changeover mass) the train stops after less than 80 m as shown in Figure 4. For such distances sensors are available.

5 Conclusion & Future work

The presented hardware and software is able to detect obstacles and measure their distance to the train on straight tracks. Pedestrians without reflective vests can be classified with high probability. This has been proved in various experiments. With the help of the braking curves, braking distances can be calculated and collision warnings due to detected obstacles can be displayed.

In the near future, the manually labelled data can be used to train a NN in order to detect railway specific objects like relevant signals and people with reflective vests. In addition, detected tracks will be used to enable the point cloud algorithms to find obstacles in curves, too.

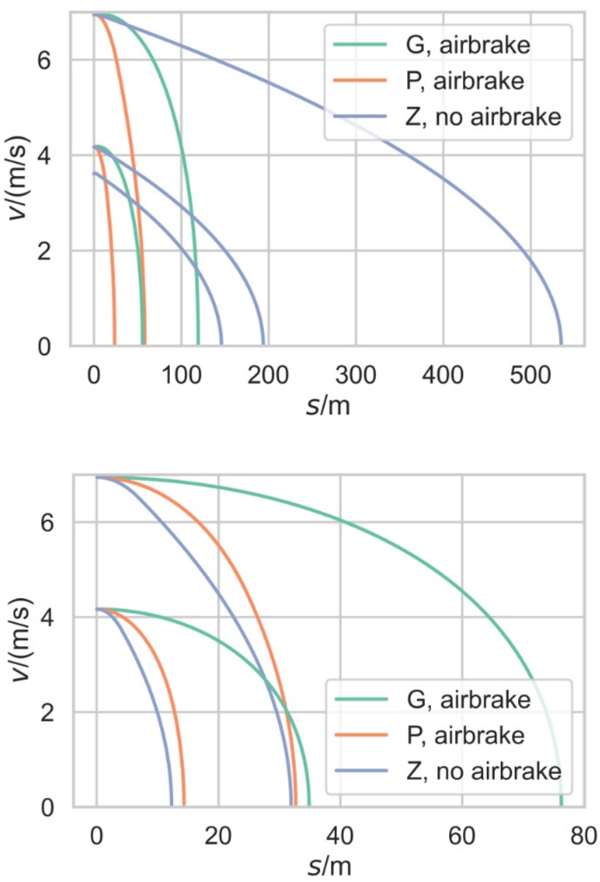

Figure 4. Braking curves worst case (top) and best case (bottom).

References

1. D. Ristic-Durrant, M. A. Haseeb, D. Emami, A. Gräser, V. Nikolić, I. Ćirić, M. Banić, B. Brindić, D.Nikolić, D. Radovanović, F. Eßer, C. Schindler : SMART concept of an integrated multi-sensory on-board system for obstacle detection. In: *Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, Vienna, Austria*, (2018).
2. J. Gleichauf, S. May: Obstacle Avoidance System for an Autonomous Shunting Locomotive, *Applied Research Conference in Glasgow*, (2017).
3. R. B. Rusu, S. Cousins: 3D is here: Point Cloud Library (PCL). In: *IEEE International Conference on Robotics and Automation (ICRA)*, (2011)
4. M. Ullah, A. Mohammed, F. Alaya Cheikh: PedNet: A Spatio-Temporal Deep Convolutional Neural Network for Pedestrian Segmentation. In: *Journal of Imaging*, **4** (2018).