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# Detection and Tracking of Moving Objects Using 2.5D Motion Grids

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***Abstract*—Autonomous vehicles require a reliable perception of their environment to operate in real-world conditions. Awareness of moving objects is one of the key components for the perception of the environment. This paper proposes a method for detection and tracking of moving objects (DATMO) in dynamic environments surrounding a moving road vehicle equipped with a Velodyne laser scanner and GPS/IMU localization system. First, at every time step, a local 2.5D grid is built using the last sets of sensor measurements. Along time, the generated grids combined with localization data are integrated into an environment model called local 2.5D map. In every frame, a 2.5D grid is compared with an updated 2.5D map to compute a 2.5D motion grid. A mechanism based on spatial properties is presented to suppress false detections that are due to small localization errors. Next, the 2.5D motion grid is post-processed to provide an object level representation of the scene. The detected moving objects are tracked over time by applying data association and Kalman filtering. The experiments conducted on different sequences from KITTI dataset showed promising results, demonstrating the applicability of the proposed method.**

## I. Introduction

The interest in autonomous cars which are able to perceive environment and take appropriate actions, has increased significantly in recent years. However, to increase their reliability and capability to operate in real-life environments they need to be empowered with a stronger representation and understanding of their surroundings. Different types of sensors such as stereo vision [1], [2] and 3D laser scanners [3], [4] are employed along with radars [2], [5] to perceive the environment in 3D. The data acquired by these sensors need to be processed to build an internal representation of the environment surrounding the vehicle. Using this representation an intelligent vehicle can take an appropriate decision in response to the state of its surrounding environment.

Autonomous road vehicles must be able to perceive the dynamic environments and detect moving objects such as vehicles and pedestrians. By detection, tracking and analyzing the moving objects, an autonomous vehicle can make a prediction about objects' locations and behaviors and plan for next actions. Detection and tracking of moving objects (DATMO) is a rapidly developing field that provides awareness of road scene participants for intelligent vehicles.

In this paper, we propose a DATMO approach based on a 2.5D grid-based representation of the dynamic environment surrounding a vehicle equipped with a 3D laser and a GPS/IMU system. The proposed method comprises two main parts: 1)- detection of moving objects; 2)- data association and tracking of moving objects. The main contribution of this paper is on the first part where a robust motion detection mechanism is proposed that can handle small localization errors and suppress false detections using spatial reasoning. The motion grids are next used to extract moving objects. The proposed method detects moving objects in the absence of a priori assumption on the shape of the objects which makes it suitable for a wide range of targets like pedestrians, vehicles, or bicycles. The result of the proposed method is the 3D bounding box of moving objects.

The remaining part of this paper is organized as follows. Section II describes the related state of the art methods. Section III describes the proposed DATMO approach by means of a 2.5D motion grid algorithm. Experimental results are presented in Section IV and Section V brings some concluding remarks.

## II. Related Work

Different techniques have been proposed for the detection and tracking of moving objects. In Petrovskaya et al. [6] DATMO approaches are classified into: traditional DATMO, model-based DATMO and grid-based DATMO. Here, we are interested in the grid-based approaches. Grid-based approaches are a memory-efficient environment representation that makes them a good choice for integrating temporal data. Grid-based DATMO starts by making a low-level grid representation of the dynamic environment, followed by segmentation and tracking, to provide an object level representation of the scene. The Bayesian Occupancy Filter (BOF) [7] is a well-known grid-based DATMO. It adapts Bayesian filtering to the occupancy grids to infer the dynamic of the grids and in combination with the Fast Clustering and Tracking Algorithm (FCTA) [8] is used for detection and tracking of moving objects. Recent work [9] introduces a motion detection module to improve FCTA performance. However, setting the parameter values of the FCTA is a challenging task. Other approaches exist in the literature for perception and reasoning of the dynamic environments. Moras et al. [10] build a 2D polar grid using 2D laser and GPS/IMU positioning system and detect moving objects by conflict analysis of evidence grids. It works based on the fact that a moving object occupies different cells along time. Based on Dempster-Shafer theory, the motion of an object is represented by conflicting information that results in detection of moving objects. This method needs very precise ego-motion estimation and finding appropriate values of the method's parameters is not straightforward. Li and Ruichek [11] proposed a stereo-vision based framework to build up a dynamic occupancy grid map. First, feature points are extracted

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TABLE I: Some recent related work on the perception of dynamic environment surrounding a vehicle.

| Reference | Sensor | Representation | Motion/clustering/segmentation | Data association and tracking |
|---|---|---|---|---|
| Baig *et al.*, 2014 [9] | Stereo vision and 2D lidar | 2D occupancy/velocity grid and odometry | Motion detection by transferring occupancy information between consecutive grids using odometry data and integration with BOF and Fast Clustering and Tracking Algorithm FCTA) | |
| Moras *et al.*, 2011 [10] | 2D lidar | 2D polar evidence grid and GPS/IMU odometry | Motion detection using conflict analysis in evidential grids | — |
| Li and Ruichek, 2014 [11] | Stereo vision | 2D occupancy grid, feature points and visual odometry | Motion estimation based on feature points. Dynamic grid mapping and moving object detection and segmentation using disparity images | — |
| Nguyen *et al.*, 2012 [12] | Stereo vision | 2D occupancy grid and odometry | Hierarchical segmentation method to cluster 2D grid cells into object segments | Gating, distance-based data association and Interacting Multiple Model (IMM) tracking |
| Vu *et al.*, 2011 [5] | 2D lidar and radar | 2D occupancy grid, odometry and fast scan matching | Motion detection based on inconsistencies on local map | Multiple Hypothesis Tracking (MHT) with an adaptive IMM filter |
| Pfeiffer and Franke, 2010 [13] | Stereo vision | Stixel (2.5D vertical bars in depth image) and visual odometry | Segmentation of stixels based on motion, spatial and shape constraints using graph cut algorithm | Kalman filter |
| Broggi *et al.*, 2013 [14] | Stereo vision | 3D voxel grid and visual odometry | Distinguish stationary/moving objects using ego-motion estimation and color-space segmentation of voxels | A greedy approach based on a distance function and Kamlan filter |
| Azim and Aycard, 2014 [15] | Velodyne laser scanner | Octomap, odometry and scan matching | Inconsistencies on map and density based spatial clustering | Global Nearest Neighborhood (GNN) and Kalman filter |

and matched. Next, the inlier and outlier points, which are related to the moving vehicle/objects, are identified. Ego-motion is estimated based on inlier feature points. Outliers are used as seeds and a flood-fill segmentation method is applied to segment independent moving objects in the U-disparity map. Finally, they build up a dynamic occupancy grid map by combining segmented moving objects and the estimated occupancy probability. Nguyen et al. [12] used a stereo camera to build a 2D occupancy grid map and applied a hierarchical segmentation method to cluster grid cells into object segments. In the process for building the occupancy grid, the first detected occupied cell is initialized as the first segment. Next, based on a proximity constraint and a distance function, other detected occupied cells are added to the same segment or used to create a new segment. An Interacting Multiple Model (IMM) based tracking, which is able to consider more than one motion model for a moving object, was adopted. Vu et al. [5] proposed a DATMO approach relying on a simultaneous localization and local mapping procedure. Odometry data in combination with a fast scan matching algorithm are used to provide localization. Moving objects are detected based on the inconsistencies between observed free space and occupied space in the local map. Detected moving objects are tracked using a gating strategy and a Multiple Hypothesis Tracker (MHT) coupled with an adaptive Interacting Multiple Model (IMM) filter. Pfeiffer and Franke [13] proposed the Stixel representation, consisting on sets of thin, vertically oriented rectangles. Stixels are segmented based on the motion, spatial and shape constraints and tracked using the 6D-vision Kalman filter framework that is a framework for the simultaneous estimation of 3D-position and 3D-motion. Broggi et al. [14] used ego-motion to distinguish between stationary and moving objects, followed by a color-space segmentation of voxels that are above the ground plane. Voxels with similar features are grouped together. Next, the center of mass of each cluster is computed and Kalman filtering is applied for estimating their velocity and position. Azim and Aycard [15] proposed a method based on the inconsistencies between observation and local grid map using Octomap [16] representation. Octomap is a 3D occupancy grid with an octree structure. Next, they segment objects using density based spatial clustering. Finally, Global Nearest Neighborhood (GNN) data association, and Kalman filter for tracking, and Adaboost classifier for object classification are used. The summary of the aforementioned methods is shown in Table I. Most of these approaches work well under the condition of low measurement noise. Inaccuracy in ego-motion estimation and noisy measurements, frequent in real-world dynamic environment, can lead to misinterpretations and false detections.

This paper contributes with a robust 2.5D grid-based motion detection algorithm that is able to handle small localization errors. An efficient 2.5D grid-based DATMO is proposed,

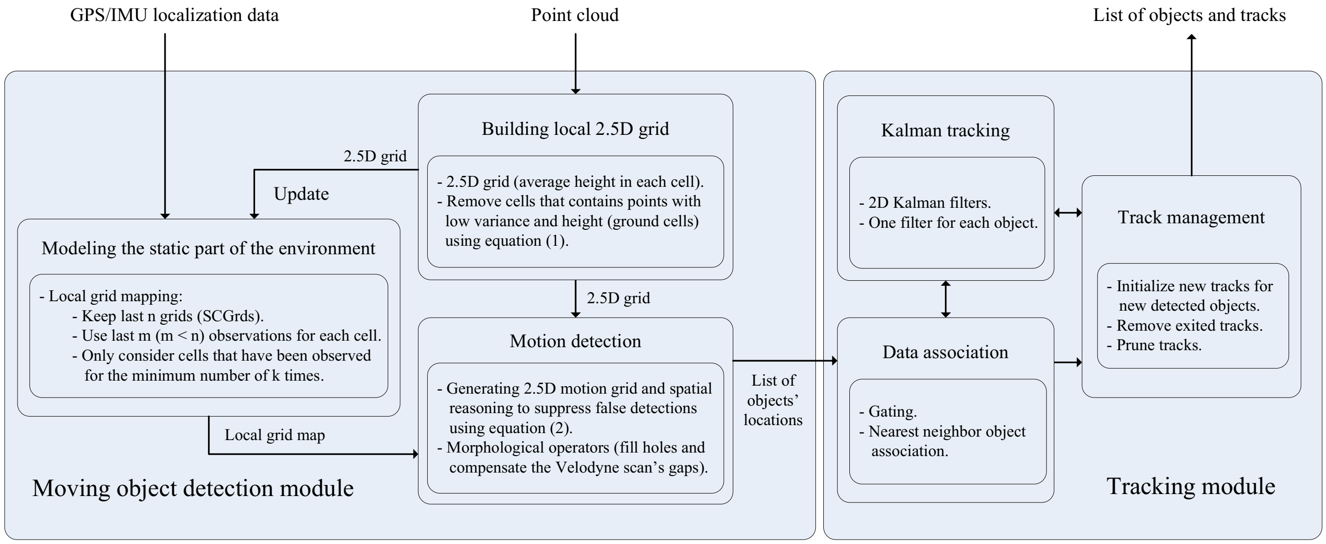


Fig. 1: Architecture of the proposed algorithm for 2.5D grid-based detection and tracking of moving objects (DATMO).

which outputs a list of objects' 3D bounding boxes and tracks, but, avoiding a computationally expensive full 3D representation of the environment. It extracts moving objects from 2.5D motion grids without a priori knowledge about objects.

## III. Proposed Method

In this section, we present an algorithm for 2.5D grid-based DATMO. Fig. 1 shows the architecture of the proposed perception system. Each block is described in the following sections.

### A. *Building a local 2.5D grid*

A 2.5D grid stores in each cell of a discrete grid the height of objects above the ground level at the corresponding point of the environment [17]. For a vehicle moving on a single underlying surface, a 2.5D grid provides sufficient information to represent the surrounding environment. Obstacles overhanging at higher levels than the vehicle, such as bridges, are ignored without compromising safety.

In the present work, we are going to build a 2.5D local height grid to continuously represent an area covering 30 meters ahead of the vehicle, 10 meters behind it and 10 meters on the left and right sides of the vehicle. The grid resolution in the vehicle plane is chosen to be equal to 20 $cm$ providing enough number of cells to represent objects. The total number of 2.5D cells inside the local grid is $20,000$. For each cell, the height value is determined by calculating the average height of all measured points mapped into the cell.

Those cells that belong to the ground can cause false detections, in motion detection module, particularly in the case of undulated roads. A simple method is used to remove ground cells when building the 2.5D grid. The variance of height of points falling into each cell is computed. If the value is under a certain threshold, it is selected as a candidate of a ground cell. However, this cell may belong to any planar surface such as the roof of a vehicle. A cell is confirmed as a ground cell if its average height is lower than a given threshold. To summarize, a cell belongs to the ground if it has a variance and height lower than certain given thresholds. A 2.5D grid with rejection of ground cells is computed by

$$Grd[i] = \begin{cases} 0, \; if \; \sigma_i^2 < tr_\sigma \; and \; \mu_i < tr_\mu \\ \mu_i, \; otherwise \end{cases} \tag{1}$$

where $\mu_i$ and $\sigma_i^2$ are the average height and its variance in cell $i$. The $tr_\sigma$ and $tr_\mu$ thresholds are learned empirically, and in our experiments were chosen as 2 $cm$ and 30 $cm$ respectively. The result of this stage is a 2.5D grid with removed ground cells.

### B. *Modeling the static part of the environment*

So far, we addressed the problem of building a local 2.5D grid using data collected at one instant of time. The next step consists on the integration of consecutive 2.5D local grids and GPS/IMU localization data to build a local 2.5D map. This map is particularly useful to model the static part of the environment. The 2.5D grid map is updated on every new 2.5D grid obtained from new sensor data.

To keep the number of necessary computations limited and to avoid problems resulting from the accumulated error of localization drifts, the number of possible 2.5D grids is limited by considering only a time slot instead of the whole history. Therefore, old 2.5D grids are discarded after $n$ scans. A queue like data structure is defined using a first in first out (FIFO) approach to keep a sequential collection of 2.5D grids $SCGrds$ (with a maximum length of $n$). Using this structure, we keep the last $n$ grids which are permanently being transformed according to the current pose of the vehicle. The 2.5D map is calculated for each cell by taking the average on the maximum number of $m$ last valid values in the cell's history with a constraint that a cell should have been observed

**Inputs:** The local 2.5D grid generated from the last Velodyne laser scanner's point cloud with pose of the vehicle in Euclidean space given by GPS/IMU measurements; length of the sequential collection of grids (maximum length of the history) $n$; maximum number of integrated grid cells $m$.

**Output:** The 2.5D map that models the static part of the environment surrounding the vehicle.

**start**

Remove the oldest 2.5D grid from the bottom of the collection $SCGrds$.

**for** $n-1$ to 1 (from bottom to top)

Grab corresponding 2.5D grid from the collection $SCGrds$ and transform it into the current coordinate system of the vehicle.

Move the transformed 2.5D grid downwards in the collection $SCGrds$.

**end**

Insert the new 2.5D grid at the top of the collection.

For every local map's cell compute the average of the $m$ most-recent corresponding cell values in the collection.

**end**

Fig. 2: Local 2.5D map updating process.

for a minimum $k$ number of times. The $n$, $m$, and $k$ values were chosen as 50, 30, and 3 respectively. The algorithm steps are shown in Fig. 2.

### *C. A robust 2.5D motion detection*

In this section, we present a method for robust 2.5D motion detection followed by a motion grouping mechanism to extract an object level representation of the scene.

In ideal conditions, motion detection could be performed simply by subtracting the last 2.5D grid from the 2.5D map of the environment. However, in practice we have a moving vehicle on an undulated road, suffering from localization errors. Therefore, a simple subtraction results in many false detections. We divide false detections in two categories: 1)- false detections on the ground plane due to the non-uniform nature of the road, which is solved in the 2.5D grid building phase by removing ground cells; 2)- false detections due to small localization errors that are usually spatially clustered in the grid. Inspired by [18], we adopted a spatial reasoning to reduce the occurrence of the second category. After updating the local map using the last 2.5D grid, the 2.5D motion grid is calculated using the following formula:

$$Mtn[i] = \begin{cases} Grd[i],\ if\ min|Grd[i] - Map[I]| > tr_\delta \\ 0,\ otherwise \end{cases} \qquad (2)$$

where $Grd$, $Map$, and $Mtn$ are the last 2.5D grid, 2.5D map, and 2.5D motion grid. $I$ indicates a vector containing indexes of cells in the neighborhood of cell $i$. The size of the neighborhood radius was considered as being of 5 cells, which is a sufficient number of cells to compensate for a maximum localization error of $1\ m$. Each $i$ cell in $Grd$ is labeled as being in motion or being a false detection by comparing its value with the corresponding neighborhood area on the map. If the grid cell has a value close to the neighborhood cells, it is labeled as a false detection, otherwise it is part of the motion. $tr_\delta$ is the maximum acceptable distance between cell values, which is empirically set to $\alpha \times Grd[i]$. Coefficient, $\alpha$, can take a range of values from $0.2$ to $0.5$. With this approach, we are able to eliminate many false detections caused mainly due to localization errors. Some small and sparse false detections can still remain, but they are eliminated by applying post-processing.

For object extraction from motion grids, we used mathematical morphology, which is a technique for the analysis and processing of geometrical structures. A two-level morphology is employed on the 2.5D motion grid for two purposes: filling small holes inside the object motion representation, and to compensate for the existing gap between Velodyne scans. A basic dilation operator with rectangle structure is applied in $x$ and $y$ directions to fill the small holes inside object motion. The results of dilation in $x$ and $y$ directions are multiplied together to keep false detections small. The gaps between Velodyne laser scans, particularly in the vehicle movement direction, may cause a detected object to be split into different sections. Therefore, a second dilation operator is applied in the car movement direction to fill the gaps between Velodyne laser scans. Finally, we do some post-processing to remove very small sized and unusual size regions and label connected components. The labeled connected components that correspond to moving objects are inputted to the tracking module. At this stage, we can easily compute the 3D bounding box of each moving object, using the size and maximum height of each connected component. Fig. 3 shows results of the different steps involved in motion detection module.

### *D. Kalman filtering*

The centroid of each labeled group of motions (object) obtained from the motion detection module (see Fig. 1 and Fig. 3-iii) is assumed as the location of each detected moving object. Kalman filter with constant velocity model is used for the estimation and prediction of each target location in the next frames. A new 2D Kalman filter is associated for every new detected moving object.

### *E. Data association*

Gating and nearest neighbor strategies are used to determine which detected object goes with which track. First, a gating strategy is applied to prune candidates. If there is more than one candidate, the nearest candidate is associated with the track. If there is no candidate, it is assumed that a miss detection is occurred and the Kalman filter prediction is used, and a flag is sent to the track management for further actions. Those objects that are not associated with any existing track are forwarded to the track management process.

### *F. Track management*

The main objectives of track management are: initialization of a new track for every newly detected object, removing

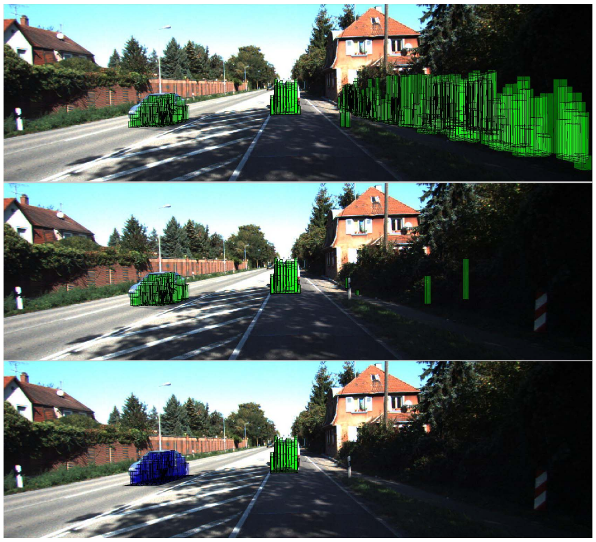

Fig. 3: From top to bottom: i) 2.5D motion grid obtained by simple subtraction of last grid from map, ii) after false detection suppression, iii) after morphology, post-processing, and labeling connected components. For a better visualization, the 2.5D grid was projected and displayed onto the RGB image.

exited tracks when their location falls outside the local grid and pruning tracks.

The data association module sends information to the track management unit in two situations: i) when there is a new object that is not associated to any existing track, and ii) when there is no object for association to a track. When a new object is detected, not yet associated to a track, it might be a true or a false detection. In this case, the track management unit creates a new track and waits for the next frame; if in the next observation an object get associated to that track it is confirmed as a new object, else it is considered as false detection. For the second situation, when there is no object to associate to a track for next consecutive frames, that track is eliminated.

## IV. Experimental Results

The presented algorithm was tested on a set of data acquired with a real vehicle. The proposed method is currently implemented in Matlab and runs offline. The ground truth for the specific task of DATMO is not available yet, therefore we have performed a qualitative evaluation. In the following sections we describe the dataset used to evaluate the proposed method and present experimental results.

### A. Dataset

We evaluated the proposed method using the KITTI dataset [19]. This dataset was captured in rural areas and highways using a car equipped with multiple sensors. The data used was recorded using a Velodyne 3D laser scanner and a high-precision GPS/IMU inertial navigation system.

The Velodyne HDL-64E rotating 3D laser scanner spins at 10 frames per second counter-clockwise with vertical resolution of 64 layers, angular resolution of 0.09 degree, and 2 cm distance accuracy. The horizontal and vertical fields of view are 360 and 26.8 degrees respectively, and the maximum range is 120 m. The Velodyne point cloud is compensated for the vehicle ego-motion. The inertial navigation system is a OXTS RT3003 inertial and GPS navigation system with 100 Hz speed of recording data and a resolution of 0.02m / 0.1 degree.

### B. Evaluation

In order to evaluate the performance of the proposed algorithm, a variety of challenging sequences were used. The most representative sequences are summarized in Fig. 4. This figure is composed of two kinds of representations: the RGB screenshot of the scene and the grid representation of the scene. The 2.5D motion grid, 3D bounding box and tracks of moving objects are shown in the grid representation. The blue dots correspond to the Velodyne points and vectors on the center of the local grid show the pose of the vehicle. Only the 3D bounding of detected moving objects are shown in the RGB image. The selected sequences are: 1)- vehicles circulating on a highway; 2)- a road junction scenario; 3)- a crossing scenario. In the first scenario, the proposed DATMO system detects and tracks all the moving vehicles when they get into the local perception field. In the road junction scenario, in the early frames a vehicle comes from different lane and in the next frames two vehicles join to the road. Our method successfully detects all the moving objects. In the crossing scenario, the proposed DATMO system successfully detected the vehicles passing by.

## V. Conclusion

Awareness of moving objects is one of the key components for the perception of the environment. In this paper, we propose a 2.5D grid-based DATMO. A 2.5D grid, with excluded ground cells, was employed for the representation of the environment. Each cell value is computed by averaging the heights of all measured points mapped in the cell. A robust motion detection mechanism was introduced to handle false detections caused by small localization errors. First a model of the environment surrounding a vehicle was developed. In every frame, the last generated 2.5D grid is compared with the updated environment map to generate the 2.5D motion grid. A method was presented aiming to suppress false detections, due to small localization errors, based on spatial reasoning. The object level representation is achieved by grouping the motion grids. Moving objects are detected without a priori knowledge about them. Detected moving objects are finally tracked using gating and nearest neighbor association strategies and Kalman filtering. Experimental results are presented that give good indication of the applicability of the proposed DATMO system. We plan to make the system more robust, less dependent on thresholds assigned empirically, and to assess its performance in real-time applications.

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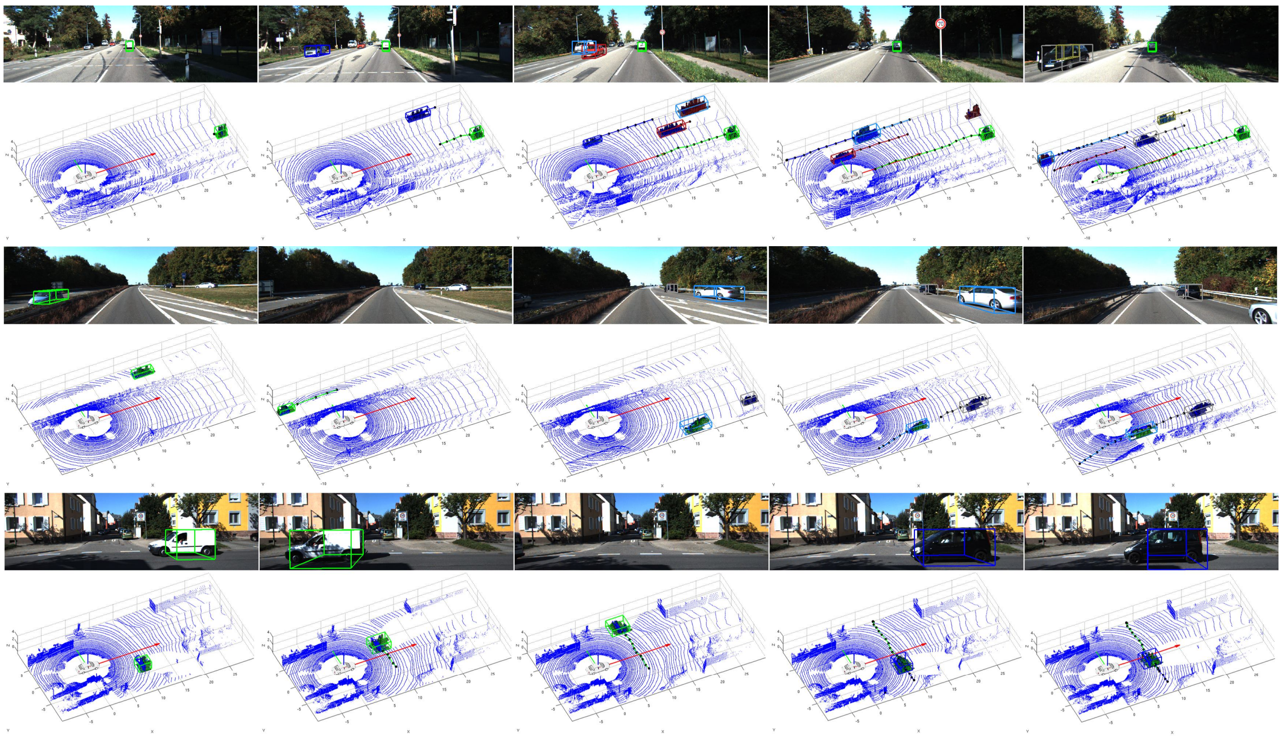

Fig. 4: Sample screenshots of the results for the sequences. Each raw represents one sequence. From top to bottom, results for: vehicles circulating on a highway; a road junction scenario, and a crossing scenario. Left to right we see the results obtained in different time instants.

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