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ELROB 2018 – Convoy and Mule of Team MuCAR

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***Abstract*— We present the hard- and software components of team MuCAR's fully autonomous vehicles to participate at the ELROB 2018 in the convoy and mule scenarios.**

For the convoy scenario, different tracking approaches are applied to track the leading vehicle. Data association of the tracking results is done in a PHD filter framework. Given the resulting estimate, an optimization-based planning module computes kinematically feasible trajectories to follow the leading vehicle's path as close as possible with a velocity-dependent lateral distance.

In the mule scenario, the leading guide is tracked either with a LiDAR-based Greedy Dirichlet Process Filter (GDPF) approach or in a vision-only approach by segmenting the disparity image and reprojection into 3D space to match the existing track. During the shuttling phase, two environment modeling algorithms were implemented. Again, one mapping approach is based on LiDAR and the second is based on vision only. The LiDAR mapping approach includes besides occupancy, color information, heights and terrain slopes. In the vision-only mapping approach a dense disparity image with a tri-focal camera is generated and back-projected to create a virtual 3D scene.

Finally, a high-level mission planning module and a local trajectory planner are used for GPS-based autonomous shuttling. The local trajectory planner based on a hybrid A* approach incorporates data from the environment mapping modules for goal-oriented navigation and local obstacle avoidance.

I. Robotic Platforms

Team MuCAR consists of 13 research assistants working at "Autonomous Systems Technology" institute at the University of the Bundeswehr Munich, whose chair is Prof. Dr.-Ing. H.-J. Wuensche. We participated with large success in various competitions such as ELROB 2007–2010, 2012, 2016 and euRathlon 2013, where we took 1st place in the "Autonomous Navigation" scenario. Further, together with TU Karlsruhe and TU München, we competed as part of Team AnnieWAY in the DARPA Urban Challenge 2007, where we were one of only 11 teams which made it into the finals.

Our institute has two autonomous vehicles with full drive-by-wire capabilities, named MuCAR-3 and MuCAR-4 (Munich Cognitive Autonomous Robot Car, see Figure 1). MuCAR-3 is based on a stock VW Touareg with a V6 TDI engine, modified to allow computer control of the steering, brake, throttle and automatic gearbox. Full body skid plates allow for testing in rough terrain. MuCAR-4 is based on a VW Tiguan and equipped with a custom-made drive-by-wire system as well. Since the hardware is either mounted inside the vehicle or protected with an appropriate housing, the vehicles are able to act in fog or rain.

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(a) MuCAR-3. (b) MuCAR-4.

Fig. 1: The 3rd and 4th generation of the Munich Cognitive Autonomous Robot Car (MuCAR).

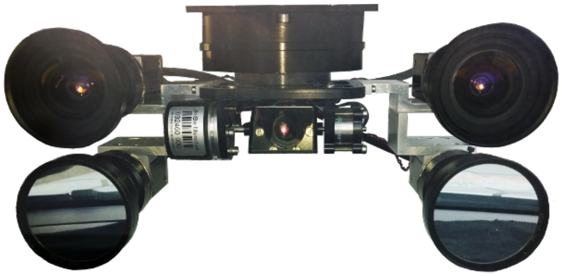
A detailed description of the vehicles' hard- and software follows in the next sections.

A. Sensors

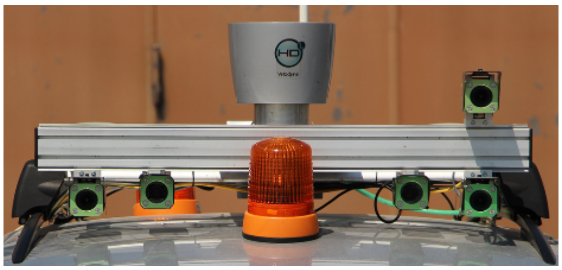
Basic sensors for e.g. the steering-wheel angle or the wheel speed are available in the stock car and can be used for autonomous driving. The sensing of the vehicle was extended with the following three main components:

1) LiDAR: MuCAR-3 and MuCAR-4 are equipped with a Velodyne HDL-64E S2 LiDAR, which is mounted on the roof of each vehicle. It consists of 64 single laser beams rotating around a common axis at 10 Hz. This commercially available sensor provides a horizontal field of view (FOV) of 360° and a vertical FOV of 26.8°. Its horizontal and vertical resolutions are 0.09° and 0.4°, respectively. Additionaly, MuCAR-3 is equipped with a forward-looking, close-to-production 110°-LiDAR from Ibeo which provides raw 3D points and tracked objects.

2) Vision System: MuCAR-3 and MuCAR-4 use MarVEye-8 [1], a multifocal active/reactive vision system, which is mounted between the windshield and the rearview mirror of each vehicle (see Figure 2). MuCAR-3's platform is equipped with a stereo pair of GigE Basler Ace color cameras and a Basler Ace near-infrared (NIR) camera, MuCAR-4's platform is equipped with a stereo pair of GigE Point Grey color cameras. All those cameras are equipped with wide angle lenses. For a wide field of view, MuCAR-4 is equipped with a custom-made forward-looking tri-focal stereo camera system on the roof, a Vislab stereo camera covers the rear area (see Figure 2). The tri-focal stereo system is operated by a self-developed algorithm optimizing a residual over all three images simultaneously. To extend the range of application, MuCAR-3 is equipped with a



(a) Camera platform of MuCAR-3.



(b) Custom tri-focal camera platform of MuCAR-4. The outmost cameras are used for matching.

Fig. 2: The camera platforms MarVEye-8 of MuCAR-3 and MuCAR-4 are equipped with two color cameras (upper row) and a third color camera which is mounted into the hollow shaft. In addition, MuCAR-3 has a near-infrared camera. MuCAR-4 is equipped with a roof rack and a custom made tri-focal wide baseline stereo system.

thermal camera operating in the far-infrared (FIR) spectrum and with a low light (LL) color camera.

3) Inertial Sensors: The main sensor for localization and estimation of motion is an inertial navigation system by Oxford Technical Solutions. Three acceleration sensors and gyros allow estimating vehicle motion in six degrees of freedom. The inertial measurement unit is coupled with a GNSS (Global Navigation Satellite Systems) satellite receiver (GPS, GLONASS).

By combining the information of the inertial navigation system and that of stock sensors, such as wheel-speed sensors, MuCAR-3 and MuCAR-4 are able to perform robust ego-motion estimation, which compensates for short losses of the satellite link.

B. System Architecture

The overall system architecture is depicted in Figure 3, [2]. The main computing system is a multi-CPU system equipped with a dual-CPU octa-core Intel Xeon, 64 GByte memory, a Nvidia GPU and shock resistant solid-state drives. It has several interfaces for Gigabit Ethernet, CAN and RS-232 to communicate with the sensors. Real-time computer systems from dSPACE are responsible for low-level control of the vehicle and MarVEye-8 camera platform. Additionally, they provide data from stock vehicle sensors to the main computing system. Interprocess communication between the distinct applications on the main computing system is provided by the KogniMobil Real Time Data Base (KogMo-RTDB). MuCAR-4's setup is similar.

II. Convoying Scenario

This section describes our autonomous following system for the convoying scenario of the ELROB competition.

We want to participate with MuCAR-3 as an autonomous and MuCAR-4 as a manually-driven vehicle. The driver of MuCAR-4 receives a map with UTM coordinates that specify the waypoints which have to be traversed in the given order. While a safety driver will be monitoring MuCAR-3's software and hardware system, it will follow the leading vehicle completely autonomously based on sensor data.

The following sections describe the mission planning, vehicle tracking and path generation modules used during autonomous following.

A. Mission Planning

The human machine interface module of MuCAR-3 enables an operator to configure a mission, which contains the type of the convoy leader, the maximum allowed velocity and the desired velocity-dependent convoy distance.

B. Vehicle Tracking

The fundamental task for autonomous following of another vehicle is the tracking system, which is described in the following two subsections.

1) Sensors and Systems: For that task our vehicles are equipped with several sensors as already outlined in Section I-A. On the one hand, we use a close-to-production Ibeo LiDAR and a radar sensor, which both perform internal object tracking. The output data of these sensors can be used directly.

On the other hand, we have developed two tracking algorithms which use raw sensor data from cameras and a 360°-LiDAR sensor.

For the LiDAR-only tracking, the Greedy Dirichlet Process Filter (GDPF) as described in [3] is used. The measurements for the filter are determined by first separating the ground plane from obstacle points with [4]. Second, the remaining obstacle points are clustered to coherent objects with the method of [5] and a bounding box is fitted [6] to estimate the dimension of the remaining object instances.

Another model-based method uses a manually generated 3D feature model for detection of a specific vehicle in vision and/or LiDAR data [7], [8]. It is capable of estimating the relative 3D position and orientation, the velocity and the steering angle of a convoy leader precisely. Each 3D feature model consists of significant image and LiDAR features such as vertices, edges, colored/thermal regions and occupied/non-occupied ground-plane cells. The algorithm estimates the vehicle pose of the convoy leader with a multidimensional particle filter. This particle filter generates and maintains numerous hypotheses of the convoy leader's 3D position and orientation. Then, the features of the 3D feature model are used to evaluate the hypotheses. During evaluation, hypotheses are weighted based on the feature congruency. Finally, the result of this model-based tracking approach is the particle with the highest weight which is used as an input to the object-based fusion.

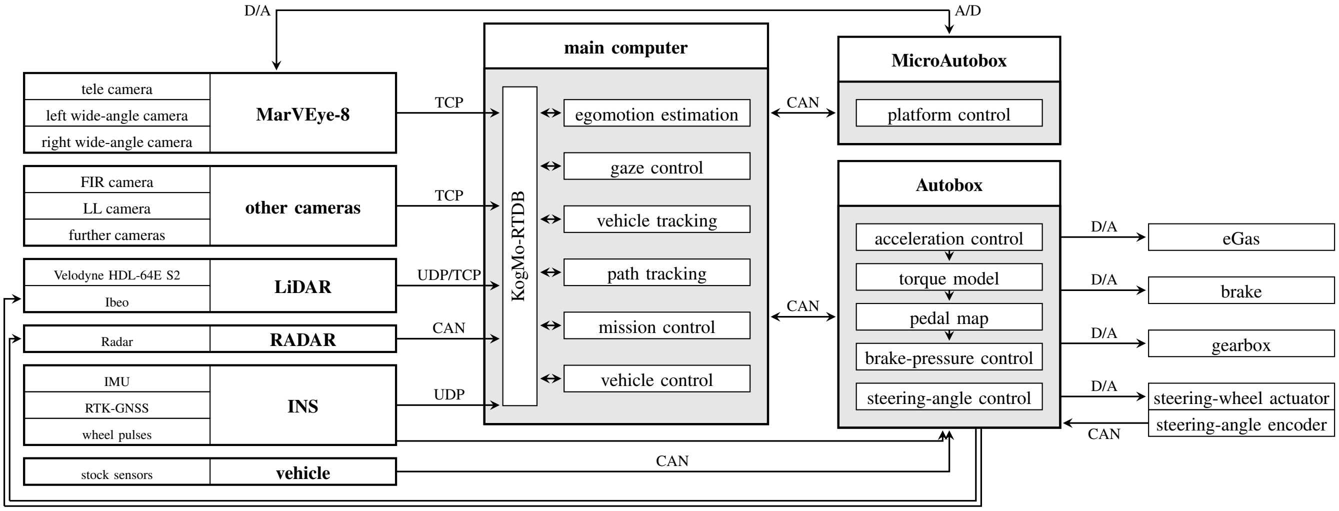


Fig. 3: Hardware architecture of Munich Cognitive Autonomous Robot Car (MuCAR) 3 and 4, taken and modified from [2].

2) Multi-Sensor Data Fusion at Object Level: In order to achieve better robustness and higher accuracy we have implemented a module which fuses the measurement data of all sensors and tracking modules at object level. Thus, it estimates the position, orientation, velocity and curvature of the leading vehicle based on a kinematic single-track model as a motion model.

Due to the huge number of detected objects which are used as input for the object-fusion module, data association is a central problem here. To solve that challenge in an elegant way, we use a Probability Hypothesis Density (PHD) filter [9], which performs data association implicitly.

The resulting output of the fusion module is an estimate for the position, orientation and velocity of the leading vehicle which can afterwards be used for path planning and vehicle control.

C. Trajectory Generation

This section describes the generation of the trajectory for the following vehicle. The trajectory generation application uses the egomotion information [10] and the object-fusion module's output (see Section II-B.2) to generate a kinematically feasible trajectory. The resulting trajectory consists of a series of concatenated clothoid arcs combined with a set of desired velocities and accelerations for each of these segments. The planning algorithm is based on numerical optimization of the trajectories' parameters. The parameters are optimized such that the resulting clothoid path tracks the estimated poses of the leader vehicle as close as possible. Additionally, the velocities and accelerations are computed such that the following vehicle maintains a desired lateral distance to the leader vehicle (see [11]).

III. Mule Scenario

The Mule scenario is comprised of two phases. During the teach-in phase, the vehicle should autonomously follow a human guide to learn the route between two endpoints. Given the learned route, the vehicle then shuttles repeatedly during the second phase between the endpoints along the learned route.

In contrast to the convoy scenario, the vehicle must provide local obstacle avoidance during shuttling. Furthermore, it should be able to recover from complete path blockages by finding an alternative path to the current route endpoint.

High-level decision making, fault detection and global replanning is implemented as a hierarchical state machine. During the teach-in phase, it records and stores the path taken by the vehicle. In the shuttle phase, the path is provided as the reference path to the trajectory planning module. More details can be found in [12].

A. Teach-In

At the beginning of the mule scenario the robot follows a human guide to the first camp. Here, the same LiDAR-based tracking system as described in II-B, with a human-based prior for the GDPF, is used. In a vision-only approach, the human leader is detected and tracked based on the movable stereo platform. The resulting disparity image is segmented to extract potential tracking targets. Afterwards, the potential targets' disparities are reprojected into 3D space and matched to previously existing tracking targets. Additionally, monocular methods, such as optical flow estimation and feature-based tracking, are employed for increased robustness in the tracking stage. The result of the tracking pipeline is a path of the tracked object and shown in Figure 4.

Subsequently, the vehicle can follow the human's path. The path is stored for later use in the second part of the mule scenario, where the robot begins to repeatedly shuttle and exchange cargo between the two camps.

B. Shuttling

1) Environment Mapping: The major prerequisite – enabling a mobile robot to autonomously navigate in unknown terrain – is its ability to perceive the local environment.

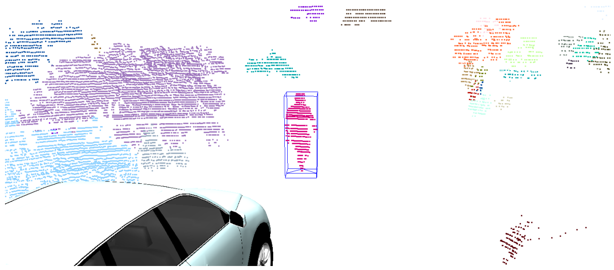


Fig. 4: Result of the LiDAR tracking system of the mule scenario. The ground plane is removed and object instances are used as measurements for the filter. Furthermore, colors of the LiDAR points correspond to the track id. The blue bounding-box denotes the sole active track, which is the human guide.

Creating some sort of environment map using its perceptual abilities thus has become a common task for nearly every robot.

For autonomous vehicles operating in outdoor environments, possibly off-road, the flat-world assumption underlying many mapping techniques is no longer valid. The approach used by MuCAR in this context is the usage of elevation maps, which store the surface of the terrain over a regularly spaced metric grid [13]. Such maps are commonly classified as $2\frac{1}{2}$D models, as every cell of the grid only stores one height value and the third dimension is only partially modeled. A high degree of detail is reached by accumulating the data from multiple complementary sensors in a single map as the vehicle moves. This way, a comprehensive, dense environment representation, including geo-referenced heights, obstacle probabilities, colors, infrared reflectivities and terrain slopes, is obtained.

Maintaining the map is efficient enough to allow building the maps online on-board our autonomous vehicle. This is achieved by an efficient method to manage the map's memory in case the robot moves, that does not need to reorganize or copy any data already stored in the map. Given all position, image and depth sensors, the aim of mapping is to produce a dense local representation of the environment, making use of all data the sensors provide. Considering the limited FOV of a (rigid) camera and the limited angular resolution of even the most advanced LiDAR sensors, a dense representation can only be achieved by accumulating data as the robot moves. For maps of limited physical size, this necessitates managing the map's data, removing data that gets out of scope and adding free map space for areas that just entered the FOV of any sensor.

Currently, each cell of the maps we build contains information about obstacles, geospatial height (both from local LiDAR sensing and from publicly available GIS-data, making use of the high-grade GPS sensor on-board), infrared reflectivity, color (from vision) and slope. Due to the different nature of sensor data, we first update the obstacle information, heights, slopes and reflectivity in parallel before updating the colors. This is because we need up-to-date heights to decide which cells are visible to the camera before updating their colors.

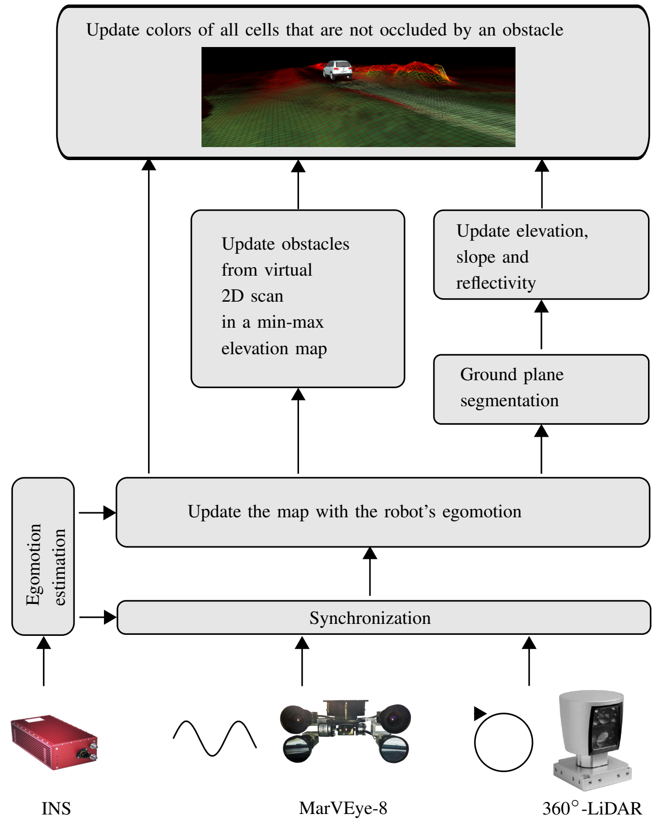


Fig. 5: Overview of the mapping architecture and the sensors involved.

In contrast to the sensor fusion based approach with camera colored LiDAR information, camera only environment mapping becomes feasible. While LiDAR provides many advantages and robust measurements, it is quite expensive. Additionally, it has an active measurement principle which may prevent usage in certain situations. In a vision-only approach, the custom tri-focal camera of MuCAR-4 is employed to create a dense disparity measurement image. The pixels of the disparity image are back-projected to create a virtual 3D scene. Each timestamp the virtual scene is rendered with a GPU to create an expected disparity measurement image. The position of the structures in the virtual scene are filtered over time to minimize the difference between expected disparity image and measured one. Afterwards, the virtual scene is used to create an obstacle grid similar to the one described by the LiDAR section.

Based on this map, a trajectory planning algorithm ensures the robot avoids obstacles and drives along the given path between the camps.

2) Trajectory Planning: The trajectory planning algorithm is described in detail in [14]. It is a variant of Hybrid A* that constructs continuous-curvature trajectories from fixed-length clothoid arcs.

Given a goal pose around 25 meters ahead of the vehicle on the global reference path, the planner attempts to find a trajectory that takes it close to the goal without necessarily reaching it exactly, which makes it robust against GPS errors. The cost function considers features such as curvature, change of curvature, proximity to obstacles, slopes, road probabilities and vegetation probabilities. As the clothoid arcs' curvatures and change of curvature are limited based on the vehicle's speed, its current and maximum steering angles as well as the maximum admissible lateral acceleration, all paths are guaranteed to be drivable.

Once the least-cost path has been found, the planner computes a piecewise-linear velocity profile (constant acceleration along each arc) which respects the vehicle's constraints w.r.t. lateral and longitudinal acceleration.

3) Global Replanning: According to the scenario definition the current route can be blocked completely. In order to find an alternative route, a digital road network of the environment in the OpenStreetMap (OSM) format is used. After a blockage is detected, Dijkstra's shortest path search is applied to find an alternative path through a graph derived from the road network. In this graph, edges correspond to roads and vertices to intersections of the roads.

IV. Summary

This paper first described the hard- and software system of the two autonomous vehicles of Team MuCAR. Then the methods implemented to accomplish the convoy and mule scenario of the ELROB 2018 robotic trials were covered. In the case of the convoy scenario, we presented the vehicle tracking system which adopts fusion at object level by applying a PHD filter. Input to the fusion algorithm comes, among others, from a LiDAR-only tracking algorithm and a model-based tracking approach. This single estimate of the leading vehicle is then used to generate a kinematically feasible trajectory to autonomously follow the leading object. For the mule scenario, we apply either a LiDAR-only based tracking algorithm or a stereo vision approach to track the leading person and store the recorded path between two camps. Given this path, the vehicle is able to shuttle between these two camps by adopting a trajectory planner which generates drivable trajectories and performs local obstacle avoidance. Finally, replanning capabilities upon complete path blockages were covered.

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