Demonstrator: V2V Communications in Automotive Multi-sensor Multi-target Tracking

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***Abstract*—Today's automotive sensor systems for in-vehicle based target tracking, i.e. radar, lidar, camera, are limited to a field of view which is restricted by distance, angle and line-of-sight. Future driver assistance systems such as predictive collision avoidance or situation-aware adaptive cruise control require a more complete and accurate situation awareness in order to detect hazardous and inefficient situations in time.**

Therefore, we introduce multi-target tracking including Vehicle-2-Vehicle communications as a complementing sensor for future driver assistance systems. The demonstration presents set-up, functionality and results of multi-sensor multi-target tracking based on particle filtering.

I. Introduction

Future driver assistance systems require a comprehensive and accurate situation model. Often in-vehicle sensors do not provide sufficient quality and quantity of information to fulfill the demanding requirements. Vehicle-2-Vehicle (V2V) communication can be seen as an adaptive sensor that provides additional information regularly but also on demand. Due to the fact that V2V communication strongly depends on the penetration rate, we argue for a seamless integration of V2V communication as an additional sensor in automotive sensor fusion. With increasing penetration rate the sensor fusion will significantly benefit and eventually unfold its full potential. Due to the fundamentally different measuring principles of in-vehicle sensors and information provided by V2V communication, redundancy and complementarity can be leveraged to a great extent, thus, increasing accuracy, reliability and robustness of the situation assessment.

II. Technical Content

A core component of future driver assistance systems will thus be a dynamic state estimator that allows the fusion of multiple sensors and tracking of multiple targets. In [1] we propose an implementation for multi-target multi-sensor tracking based on particle filtering [2], [3]. In brief, a particle filter is a sequential Monte Carlo method that uses Bayesian inference to predict and update the state estimation on the occurrence of inaccurate and incomplete observations. In order to enable the tracking of multiple targets we use a state model that is separated in n partitions including the state estimation for n target vehicles. Each particle state hence stands for a single hypothesis which encodes a certain target constellation (qualitative as well as quantitative).

For the multi-sensor tracking, observations are given twofold:

- a list of relative positions provided by an autonomous sensor (e.g. radar or lidar)
- a list of absolute positions determined by the Global Navigation Satellite System (GNSS) distributed via V2V ad-hoc communication

This poses the question how these measurements can be associated with each other, how incomplete measurements (due to measurement errors or low penetration rates) can be handled, how wrongfully measured "ghost vehicles" can be detected and how noisy sensor measurements can be filtered. Our particle filter implementation provides a solution to cope with all these challenges. More details can be found in [1].

Fig. 1. CODAR Visualization

III. Demonstration set-up and impact

The architecture of our demonstrator is shown in fig. 2. It comprises 3 basic components:

A. CODAR Visualization

The main component of our demonstration is the *CODAR Visualization* depicted in fig. 1. The *CODAR Visualization* displays the result of the particle filter in a qualitative as well as quantitative manner. The quality of the results are directly visible in the particle/weight distribution. A changing accuracy in target tracking is stimulated by alternatively switching off the radar sensor or the V2V communication. The result will be a less accurate position estimation shown by a more widespread particle/weight distribution.

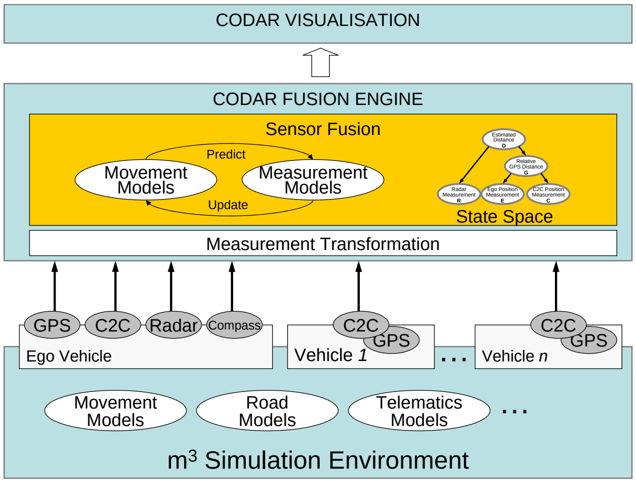

Fig. 2. System Architecture

In parallel, quantitative results, i.e. the number of tracked vehicles, are shown in the *CODAR Visualization*. An exemplary screen sequence is depicted in fig. 3. In the sequence a new vehicle approaches the field of view of the radar sensor (V2V communication is switched off in this sequence for clarity). At *t=0s* the particle filter tracks 2 vehicles which are in the field of view of the radar sensor. The number of tracked vehicles is 2 for the majority of hypotheses (hypotheses with 2 partitions are filled with black color). At *t=0.5s* the particle filter tracks an additional vehicle on the right most lane. A subset of the hypotheses already tracks 3 vehicles (particles representing hypotheses with 3 partitions are filled with gray color). Finally, at *t=1s* almost all hypotheses have 3 tracked vehicles.

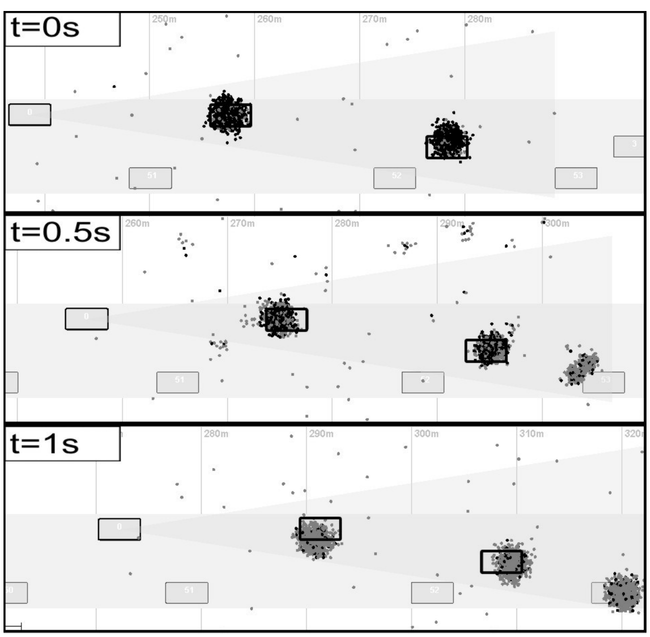

Fig. 3. Sequential Target Detection

B. *CODAR Fusion Engine*

The particle filter is part of our dynamic state estimation engine called *Cooperative Object Detection and Ranging (CODAR)* which allows a dynamic adjustment of movement models, measurement models and inference models. The impact of changes in these models can directly be seen in the *CODAR Visualization* as qualitative and quantitative changes. A more detailed explanation of the algorithms can be found in [1].

C. *Simulation Environment* m^3

In order to show the impact of influencing parameters additionally given by the application environment, i.e. signal scattering, reflection and shading, varying penetration rates, varying vehicles densities, etc. we designed a simulation environment called m^3 which allows the dynamic adjustment of parameters and models. Changes are directly reflected in the *CODAR Visualization* as qualitative and quantitative changes.

IV. Hardware configuration

The simulation hardware comprises a screen for the *CODAR Visualization* (see fig. 1), an Onboard Unit (OBU) that runs the *CODAR Fusion Engine* (see fig. 4) and a laptop that simulates the application environment m^3 (see fig. 4). Instead of real wireless V2V communication the *CODAR Fusion Engine* is connected via Ethernet to the simulation environment m^3 which simulates all sensor measurements (see fig. 2). In principle, the CODAR OBU may run in a real vehicle with real sensor connections without any substantial modifications.

Fig. 4. Simulation Setup: CODAR OBU + m^3 Simulation Laptop

V. Conclusion

Our demonstration shows the set-up, functionality and results of multi-sensor multi-target tracking based on particle filtering. The *CODAR Visualization* provides a detailed and traceable insight into our concepts. Due to the possibility to adapt model parameters on-the-fly a sophisticated study and performance evaluation can directly be shown to the demonstration attendees.

References

[1] Matthias Röckl, Thomas Strang, and Matthias Kranz. V2V Communications in Automotive Multi-sensor Multi-target Tracking. In *2nd IEEE International Symposium on Wireless Vehicular Communications*, Sept. 2008.

[2] N. J. Gordon, D. J. Salmond, and A. F. M. Smith. Novel approach to nonlinear/non-gaussian bayesian state estimation. *Radar and Signal Processing, IEE Proceedings F*, 140(2):107–113, 1993.

[3] F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P-J Nordlund. Particle filters for positioning, navigation and tracking. In *IEEE Transactions on Signal Processing*, volume 50, 2002.