# A Time-Triggered Object Tracking Subsystem For Advanced Driver Assistance Systems

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***Abstract*— Multi-sensor object tracking is an important feature for advanced driver assistance systems in future automobiles. Most state-of-the-art systems cannot guarantee deterministic processing of the sensor values due to unsynchronized sensing and processing units. To overcome this shortcoming we propose a paradigm shift towards a time-triggered system architecture providing a deterministic bus system, synchronized nodes, and a global time-base. The paradigm shift is supported by results of a simulation of different synchronization and scheduling approaches which suggest that although non-time-triggered approaches perform well in scenarios with low process noise, the time-triggered model becomes advantageous in potentially dangerous scenarios with high dynamics. In order to validate the results of the simulation for real life scenarios, we analyzed test drives derived from a testbed featuring a Volkswagen Touran being equipped with a laser scanner, a stereo camera system, a FlexRay communication system, an object tracking subsystem and a differential GPS system as reference.**

***Index Terms*— sensor fusion, object tracking, real-time, automotive, time-triggered, Flexray**

***Abstract*— Im Automobil der Zukunft spielen Fahrerassistenzsysteme eine wichtige Rolle. Ein wichtiges Untersystem sind dabei Objektverfolgungssysteme, welche andere Fahrzeuge mit mehreren Sensoren erfassen und deren Position berechnen. Die Architektur der derzeitigen Systeme kann jedoch oft weder Echtzeiteigenschaften noch Determinismus oder synchronisierte Verarbeitung garantieren. Um dieses Problem zu lösen, schlagen wir einen Pradigmenwechsel zu einer zeitgesteuerten Architektur vor. Ein simulationsgestützter Vergleich verschiedener Ansätze legte die Vermutung nahe, dass die eventgesteuerten Modelle in Szenarien mit niedriger Dynamik bessere Ergebnisse liefern, in potentiell gefährlichen Szenarien mit hoher Dynamik aber das zeitgesteuerte Modell von Vorteil ist. Um die Realitätsnähe der Simulationsergebnisse zu überprüfen, wurden beide Ansätze in einer Testumgebung mit einem Volkswagen Touran evaluiert. Das Testfahrzeug war hierfür mit einem Laser-Scanner, einem Stereo-Kamera-System, einem FlexRay-Kommunikationssystem, einem Objektverfolgungssystem und einem Differential-GPS-System als Referenz ausgestattet.**

***Index Terms*— Sensordatenfusion, Objektverfolgung, Echtzeit, Automobil, Zeitsteuerung, Flexray**

## I. Introduction

Advanced Driver Assistence Systems (ADAS) will provide increased safety and convenience for driving future cars. Example features are navigation support, cruise control, lane departure warning, collision avoidance, etc. Many of these features require the car to be equipped with sensors being able to detect obstacles and other cars and to make an accurate prediction of their position and velocity. This object tracking task can be achieved best by using multiple and possible diverse types of sensors which contribute their measurements to a sensor fusion system. While sensor fusion provides several advantages regarding accuracy, robustness, and cost-efficiency (possibility to use less expensive sensors), the approach requires coordination, communication, and computation with real-time guaranties.

The time-triggered approach (Elmenreich, Bauer & Kopetz 2003) has shown to be very effective for control, coordination, and measurement of real-time systems. The properties of a real-time control system heavily depend on the communication system. In automotive systems, two communication systems have been quite prominent in the last years: Controller Area Network (CAN) and FlexRay (Fle 2005). Although time-triggered extensions have also been proposed for CAN (Hartwich, Müller, Führer & Hugel 2000), CAN is basically an event-triggered communication system, which means that incoming data is usually processed on demand by event triggers. FlexRay provides a dynamic event-triggered communication together with a static time-triggered part. In a time-triggered system, the time for a communication or control action is fixed *a priori*, typically based on a periodical time-triggered schedule which is known to the communication partners. Thus, a time-triggered system is fully predictable at communication level. However, the average reaction time of an event-triggered system might be shorter than for a time-triggered system, since data is processed as soon as it arrives instead of at a predefined point in time. In many existing ADAS implementations the event-triggered paradigm is prevalent – a legacy of CAN-based system design. Since the time-triggered approach is expected to have advantages regarding worst-case behavior, predictability, composability, and diagnosibility, we propose a shift from the event-triggered paradigm to a time-triggered system design. In (Mauthner, Elmenreich & Kirchner 2007, Mauthner, Altendorfer, Elmenreich & Kirchner 2007, Koplin & Elmenreich 2008), we have analyzed event-triggered and time-triggered object tracking systems theoretically and by simulation. The event-triggered system operates with unsynchronized sensors and fusion cycles whose processing times vary within given lower and upper bounds while the time-triggered system operates with synchronized sensors and fusion cycles whose processing times are constant and equal to the upper bounds. The results suggest that although non-time-triggered approaches perform well in scenarios with low process noise, the time-triggered model becomes advantageous in potentially dangerous scenarios with high dynamics. In this paper we present the results of a case study implementation featuring a standard car being equipped with sensor hardware and a computing cluster in order to validate the results of the simulation for real life scenarios. The results of several test drives, although being affected by the limited possibility of exact reference measurements, confirm the feasibility of using a time-triggered approach for object tracking.

## II. Concepts and Related Work

### A. Sensor Scheduling

The scheduling of sensors has received considerable attention over the last years, especially in the fields of military (Stromberg, Andersson & Lantz 2002) and robotics (Fox 1994). This is due to the fact that in both fields multiple sensors provide object state observations for one or multiple feature services under a dynamically changing environment.

If object state observations from heterogeneous sensors are available and the environmental conditions or the demand for object state observations changes drastically over time, the activation of the most appropriate sensor set can lead to improved results (Suranthiran & Jayasuriya 2004, van Norden, de Jong, Bolderheij & Rothkrantz 2005) or the reduction of sensor usage costs (Li, Krakow, Chong & Groom 2006).

If more than one feature service requests object state observations from multiple sensors but the object state observations can either be used exclusively for one specific feature service or the resources are limited in such a way that not all requests for object state observations can be handled simultaneously, a sensor allocation has to be performed. According to Schrage et al. (Schrage & Gonsalves 2003), the goal of sensor allocation is to minimize the resource usage costs and to maximize the likelihood that all mission objectives will be completed.

In (Mehra 1976), Mehra uses different norms of the observability and the Fisher information matrix (Spall 2008) as criteria for the optimization of measurement scheduling and shows that it is preferable to cluster measurements around specific design points $t_k$.

Avitzour and Rogers (Avitzour & Rogers 1990) present a theory of optimal measurement scheduling for least squares estimation which is based on the assumption that the cost of a measurement is inversely proportional to the variance of measurement noise and that it is possible to distribute the total measurement cost arbitrarily among a set of measurements.

In (Mourikis & Roumeliotis 2006), Mourikis et al. compute the localization uncertainty of a group of mobile robots wherein the localization uncertainty is determined by the covariance matrix of the equivalent continuous-time system

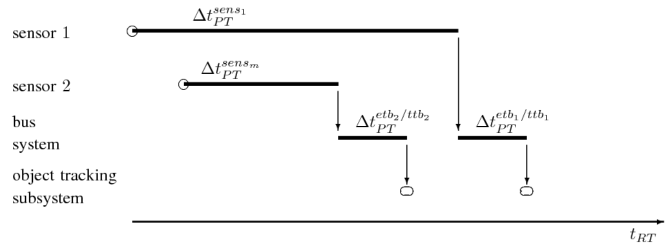


Fig. 1. Out-of-sequence measurement problem

at a steady state and is expressed as a function of the sensor measurement sampling frequencies. Based on these results, the optimal sensor sensing frequencies for each sensor on every robot can be determined and used for sensor parametrization.

However, it lacks a study of how the mean system performance is affected by a paradigm shift from a non-deterministic scheduling and transmission concept, where sensors run free and sample measurements at highest rate, to a time-triggered scheduling and transmission concept, where sensors have a fixed sampling rate and measurement time stamps can be controlled.

### B. Out-of-Sequence-Measurements

The fusion of object state observations (and related processes) is usually triggered by incoming measurements and the demand for outgoing real-time images. Often, the provision of real-time images to the feature service subsystem is fixed, because the employed control loop demands cyclic updates. Therefore, special focus is placed on the processing of incoming object state observations.

If the time stamp of an object state observation is more recent than the time instant which the associated object state represented before the prediction, the corresponding measurement is classified to be in-sequence. If the object state observation is not more recent than the instant which the associated object state represented before a retrodiction, the corresponding measurement is classified as out-of-sequence measurement (OOSM).

Figure 1 depicts a situation with an out-of-sequence measurement problem independent from communication system issues, i.e., the transmission times of object state observations from both sensors to an object tracking subsystem, $\Delta t_{PT}^{etb_1/ttb_1}$ and $\Delta t_{PT}^{etb_2/ttb_2}$, are approximately equal. Due to different observation preprocessing times, $\Delta t_{PT}^{sens_1} > \Delta t_{PT}^{sens_2}$, the measurement originating from sensor 2 is received earlier at the object tracking subsystem than the measurement originating from sensor 1, although the measurement from sensor 2 represents a more recent snap-shot of the surrounding environment.

To deal with out-of-sequence-measurements, two approaches have been extensively explored in research throughout the fusion community, i.e., the buffered (BUFF) approach and the advanced algorithms (ADVA) approach.

In the BUFF approach, measurements are stored and kept back until a chronological processing can be guaranteed. In a time-triggered system, a BUFF approach can be easily realized, but in general the BUFF approach worsens the temporal accuracy of the fused image. In the ADVA approach, a Kalman filter is used to make a prediction of the late measurements for the current system time. The ADVA approach can be realized with event-triggered and time-triggered systems, but comes with a higher complexity and requires a proper prediction model. There are several ADVA approaches that deal with one-lag and multi-lag delays, filtering and tracking, linear and non-linear systems as well as single-model and multi-model systems.

A more detailed discussion of the two approaches can be found in (Koplin & Elmenreich 2008) and (Koplin 2009).

## III. Architecture of the Object Tracking System

The object tracking subsystem consists of a laser scanner, a stereo camera system, a PC104-based processing host and a MicroAutoBox prototyping unit. The stereo camera system is a "scabor" stereo vision system developed by the technical University of Cluj-Napoca and the laser scanner is an ALASCA laser scanner from Ibeo Automobile Sensor GmbH. Both sensors provide the possibility to be operated in a time-triggered mode and have been developed for the tracking of objects in a road setting.

The laser scanner transmits its scans over a private CAN to an industrial PC (IPC) for preprocessing. The stereo camera system also sends its frames over a separate CAN to a PC-based preprocessing unit. The extracted object state observations are sent over a CAN/FlexRay gateway and the FlexRay bus to the object tracking subsystem that performs the data fusion. The fusion is processed on a PC104 system running Linux/RTAI. An object state is represented by a vector consisting of the estimated Cartesian coordinates, the moving direction of the object, the object's dimensions, and its speed and acceleration. For a maximum number of 25 observed or tracked objects, the fusion interval has been determined to be 10 ms for the given hardware resources. An update for the feature service subsystem is generated every 40 ms. After updating object states with associated object state observations, the RT images of the object states are delivered from the PC104 via FlexRay to the micro autobox, hosting the feature services.

As a reference for the tracking system, we used a Differential Global Positioning System (DGPS) mounted on the tracked vehicle. For determining the direction in which the vehicle bearing the sensors was aligned, the difference between two DGPS measurements at different spots was taken.

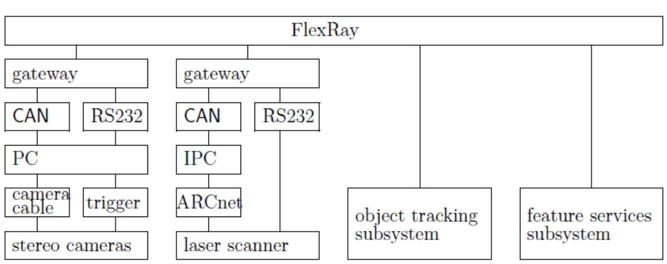


Fig. 2. System architecture

The equipment has been installed in a Volkswagen Touran (see Fig. 3). The task of the system is to measure the position of objects in front of the car. In order to increase robustness and accuracy, the measurements from both sensory systems are fused. The case study implementation supports three configurations: a BUFF configuration; an ADVA configuration; and a time-triggered synchronized configuration. For the time-triggered synchronized configuration we followed the time-triggered sensor fusion model (Elmenreich & Pitzek 2001), thus each sensor has a pre-defined measurement schedule the fusion system can rely on.

## IV. Experiment Setup

The experiment was conducted for two scenarios. In the first scenario (left part of Fig. 4), the vehicle bearing the sensors is stationary and another car accelerates in direction of the longitudinal axis of the vehicle. In the second scenario, as depicted in the right part of Fig. 4, the moving vehicle runs at a constant speed in the direction of the stationary vehicle and turns when it is around 20m ahead. In both scenarios the vehicle bearing the sensors does not move in order to avoid a cumbersome correction of the ego-motion. A test drive took about 1500 ms. During one run the tracked vehicle moved from 30 m to 40 m in the positive x direction (average speed of 6.7 m/s).

## V. Experimental Results

In this section, the results of four test drives (two for each scenario) are shown. The first test drive in each scenario represents the time-triggered unsynchronized BUFF and ADVA configuration, as both configurations use the same schedule. The second test drive represents the time-triggered synchronized configuration. The results of the test drives are depicted in Figures 5-7. Each figure consists of an RT x and an RT y plot. In each plot, object state observations from the DGPS, "dgps", are indicated by circles, object state observations from the laser scanner, "lsc", are indicated by crosses, object state observations from the stereo vision system, "scabor", are indicated by triangles, and RT images of the object state, "fusion", are indicated by squares. The arrows connect the points in time were a measurement of the laser scanner is taken and where this measurement finally has become integrated into the fused result. Fusion instants are indicated by boxed numbers.

Fig. 5 depicts the x and y plots for the time-triggered synchronized configuration in a test drive for scenario 1. In the x plot, which corresponds to the lateral axis of the car, the accuracy of the stereo vision system and the laser scanner are about the same. In the y direction, the stereo vision system yielded better results than the laser scanner. Unfortunately, in several points the DGPS showed larger variations than the actual sensors, which does not support the DGPS system as a reliable reference.

The BUFF and ADVA approach have the same underlying schedule for the sensors and the bus system and have been evaluated in the same run. Therefore, the left and right part of Fig. 6 are in the DGPS and sensor plots. However,

Fig. 3. Test vehicle and hardware installation in the trunk

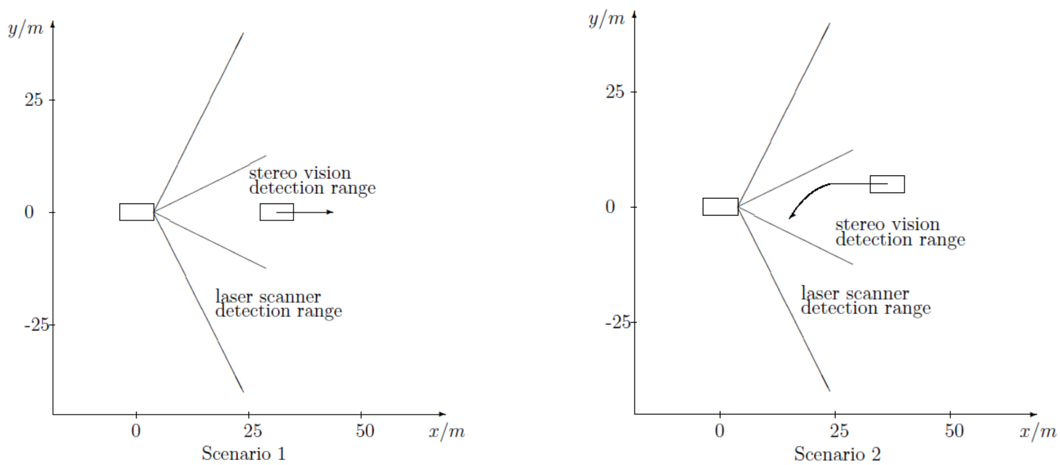


Fig. 4. Test scenarios

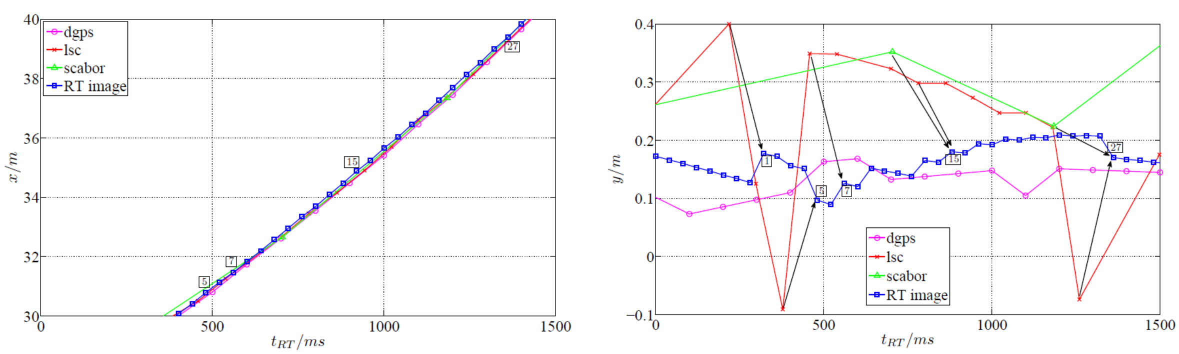


Fig. 5. Time-triggered synchronized configuration, scenario 1

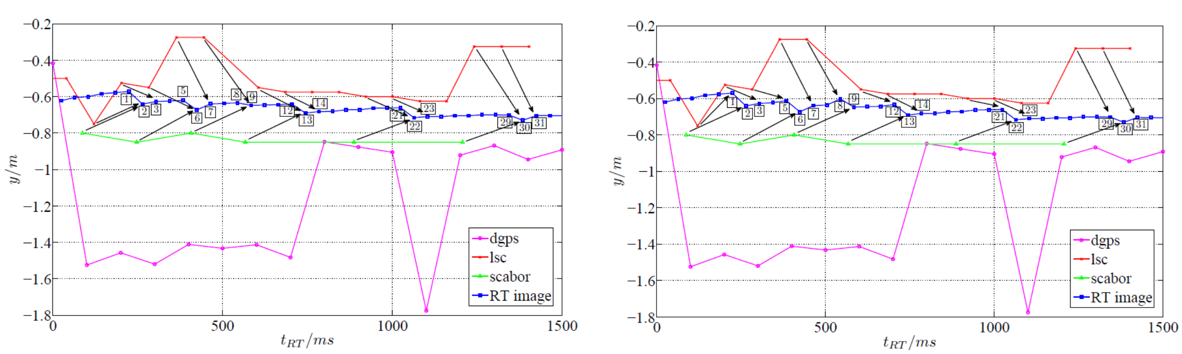


Fig. 6. BUFF vs. ADVA approach (only y-plots), scenario 1

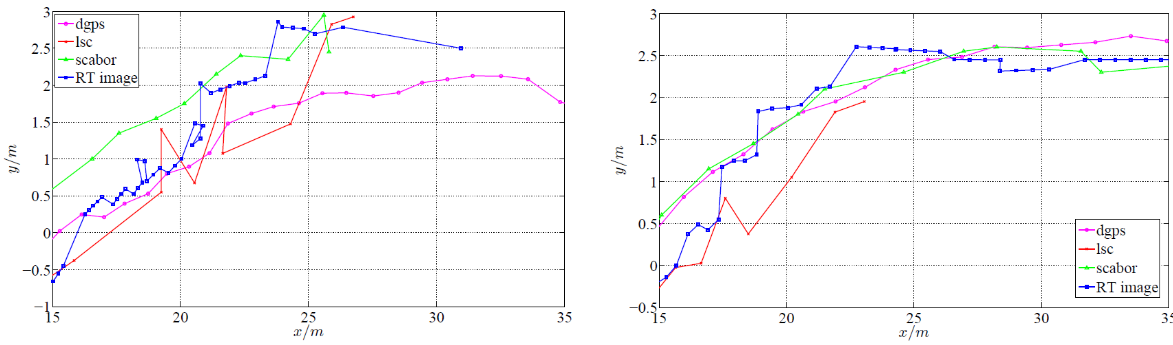


Fig. 7. ADVA vs time-triggered synchronized approach (y vs. x plots), scenario 2

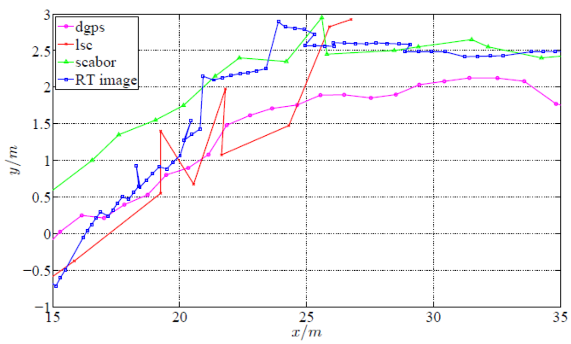


Fig. 8. BUFF approach (y vs. x plots), scenario 2

differences arise in the fusion schedule, which result in a slightly different fusion plot, which can be recognized when comparing the respective arrow indicators. Nevertheless, the differences between both approaches are too small to make a statement regarding a preferable approach.

The fused results for both runs of scenario 1 indicate variations in the same order of magnitude for all three configurations (note the different scale in Fig. 5 and Fig. 6). Due to the better sensor accuracy, the variations along the x axes are much smaller (see left side of Fig. 5).

Fig. 7 compares the results from the two runs on the second scenario for the ADVA and the time-triggered synchronized configuration. Since the moving car was turning, there is a significant movement in both directions and we present the two runs as x-y plots. The figures depict again a considerable noise on the DGPS reference and, in overall, a similar performance for both configurations. Again, the BUFF evaluation (Fig. 8) has been done concurrently with the ADVA approach which yielded very similar results.

## VI. Conclusion

The inaccuracies of the DGPS system did not allow to make predictions about the average performance of the different approaches. However, the DPGS values support the interpretation of the plots as an approximate indicator for the x and y positions. For predicting the mean performance of a particular approach, we showed in (Koplin & Elmenreich 2008) how to predict the performance based on extensive simulation results.

The achieved accuracy in the test runs is sufficient for typical ADAS applications for all configurations. Thus, even if an event-triggered approach can provide a slightly better result in some situations, the predictability of the time-triggered approach will be more important for the functionality of the system. Furthermore, the test runs show that the expected accuracy difference between the non time-triggered and the time-triggered approach is superimposed by real life non zero mean sensor signal errors. Hence, for sensors of the current generation, the time-triggered approach can be followed without experiencing a measurable performance loss. Thus, we propose a time-triggered architecture for automotive object tracking applications.

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