Virtual Sensor Simulation and Post-Processing on the Hardware-in-the-Loop Test System for Autonomous Vehicles in the Cyber-Physical Traffic System

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Abstract— **Automated driving and connected cyber-physical traffic systems present increasing challenges for the development and validation of advanced driver assistance systems and automated driving functions. In particular, real-time optimization and testing involves significant workload and risk. Providing a holistic, flexibly configurable testbed with real-time capabilities for the entire vehicle can solve this problem. However, in order to make the functionality more accurately verified by the test bench, sensor simulation is an important component, i.e., the ability to generate real sensor information in a simulated environment. In addition, the data structure of the virtual sensor, as well as the transmitting type and sampling frequency, should be close to or even consistent with that of its real sensor. In addition, we also add the noise from the real sensor to the virtual sensor. The referenced noise values are taken from the data sheet of the real sensor. This alignment enables the test bench to better test the real-time functionality of the vehicle and its ability to process the sensor signals.**

Keywords—Cyber-Physical System; Virturl sensor; Autonomous Driving; Post-Processing; Real-Time Testing

I. INTRODUCTION

Mobility is undergoing disruptive change due to the increasing digitization and networking of vehicles. The autonomous driving of electric hybrid vehicles in highly interconnected Cyber-Physical traffic systems (CPS) is one of the core technologies in this digital transformation process. The variety of applications for autonomous vehicles requires ever more diverse sensor technology, as well as ever more complex and intelligent algorithms from the fields of modern control technology and Artificial Intelligence (AI). This results in increasingly complex systems. Not only because of the increasing range of functionality, but also because of the constantly growing degree of interconnection [1].

The development of such systems is closely linked to safety engineering requirements and is therefore highly complex. In order to study the integrated overall functionality of intelligent vehicles that are capable of autonomous driving, a complete vehicle test bed is essential. This test bed should accurately represent the complete system of road, connected vehicles, and connected driving environment, as well as stimulate the vehicle's sensors. For the above reasons presented the paper [2] the concept of a holistic, highly flexibly configurable real-time test system for intelligent vehicles in cooperating cyber-physical traffic systems, called ERAGON. In a closed loop together with the function carrier AURONA, this system is able to simulate and stimulate the entire autonomous vehicle system, starting from the infusion of raw sensor data via the development and testing of AI functions up to the stimulation of realistic driving situations. Therefore, it is particularly important to test the function under test with a simulation test bed for sensor data. It is ideal for the simulated data to be bit-for-bit identical to the data generated by the physical sensor in the real-world scenario. However, this level of similarity may not be necessary or achievable. The aim of sensor simulation is to achieve a level of data fidelity that ensures the decisions made by the control algorithms are equivalent to those made in reality. Therefore, the focus should be on achieving a high level of data fidelity [3].

This paper aims to discuss the virtual sensor simulation in ERAGON, how they are transmitted, and the required post-processing and applications. The rest of the paper is organized as follows. Section II presents the holistic model-based RCP methodology for the development of complex, interconnected mechatronic systems. Section III presents state of the arts of the sensor simulation. In Section IV, the concept of the simulation of the virtual sensor and their post-processing will be introduced. Finally, Section V provides a summary of the contents as well as an outlook on further work.

II. METHODOLOGY

Through the methodology of mechatronic development, specifically mechatronic structuring, the interconnected CPS is divided into hierarchically organized subsystems across four levels of hierarchy: mechatronic functional modules (MFM), mechatronic functional groups (MFG), and autonomous mechatronic systems (AMS), and Networked mechatronic system (NMS) [4]. The outcome of this structuring is a functional decomposition of the entire system into encapsulated modules. These modules are arranged hierarchically and have clearly defined physical and informational interfaces in both horizontal and vertical directions, which lays the foundation for later integration into the overall system [5].

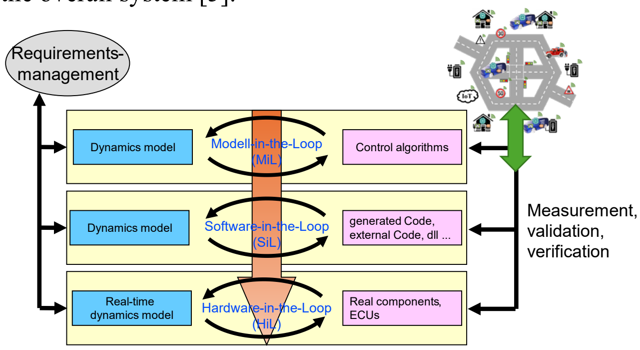

Figure 1. Seamless model-based development and validation process[6]

After establishing a hierarchical structure and specifying all interfaces, a model-based, function-centric approach is used to the design of each discrete module, adopting a bottom-up strategy. The initiation occurs at the most fundamental and critical level, the MFM, progressing upwards through the hierarchy to assimilate these modules into more complex functions. The integration and combination of these functions within the larger framework (mechatronic assembly) leverage the model-based mechatronic development cycle. Subsequently, Model-in-the-Loop (MiL) simulations are conducted to create and refine control algorithms and artificial intelligence based on a virtual or mathematical model, which are then trialed using a vehicle simulation. Within the Software-in-the-Loop (SiL) phase, these algorithms, once validated through simulation, are translated into operational code via automatic code generation, then assessed offline on a virtual platform. The sequence advances to Hardware-in-the-Loop (HiL) simulations, utilizing an augmented real-time vehicle model integrated with physical components for online verification and enhancement of the algorithms and smart functions under actual operational conditions [7]. This procedural sequence is delineated in Figure 1.

In this paper where the vehicle under test belongs to AMS due to the autonomous driving function it has, and its other underlying actuators such as motor braking are MFM. the function of assisted driving is MFG. In testing it is a HiL test because the object under test is an entity with physical components.

III. State Of Arts

Efficient functional verification is a significant challenge in realizing autonomous driving, as stated in the literature [8]. It is crucial to ensure that the functions designed in the overall system are verifiably safe in terms of output quality and the probability of misinterpretation [9]. It is necessary to repeat the tests for as many situations as possible that the vehicle may encounter. Hundreds of millions of kilometers of testing are necessary if this task is to be accomplished under real road traffic conditions [10]. Reliable and robust environment sensing through camera, RADAR, and LiDAR sensors is a key element of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD-assisted systems). Synthetic sensor data is required for driving simulations to develop and validate sensor-based algorithms. The classification of automotive sensing sensor models is based on their modeling approach and coverage effects, and can be divided into three categories: ideal, phenomenological, and physical models [11].

The Ideal Sensor Model, alternatively termed the Ground Truth Sensor Model, employs as its input an array of objects delineated within the simulation frame, as furnished by the World Coordinate System (WCS). This model, representing the epitome of accuracy, utilizes the veritable values, dimensions, positions, velocities, orientations, and bounding boxes of the simulated entities.

The Phenomenological Sensor Model operates on principles similar to those of probabilistic models, while also integrating contextual effects. This approach offers a nuanced representation of real sensor dynamics. The complexity of these models is increased by the need to incorporate special phenomena into the sensor framework, and to correlate these phenomena with context-sensitive data from the virtual environment [11].

Physical sensor models are based on physical aspects and can be numerically complex. Therefore, they may require significant computational power and may not have real-time capabilities. Subsequent models use rendering techniques provided by the simulation framework as input and generate output raw data in the form of point clouds, which contain distance, intensity and time stamps. Several rendering techniques can generate synthetic LiDAR sensor raw data, including ray tracing, ray casting, rasterization (Z-buffer), and light paths [12].

Virtual sensors have a wide range of applications in analog test platforms. Chen et al. [13] used an integrated simulation and testing platform for self-driving vehicles. Their platform offers the possibility to test real vehicles in a closed test area. Their approach is characterized by the fact that the sensor signals (GPS, IMU, LiDAR, and camera) are derived from high-precision virtual simulation scenarios and processed as real driving commands by the real control unit in the vehicle. Ying et al. [14] used an in-vehicle loop simulator and testbed to functionally validate self-driving cars Vehicle sensors (camera, LiDAR and RADAR) are stimulated by signals generated based on a virtual traffic scenario. Thus, this test environment enables repeatable and fully manageable test scenarios.

Both commercial and open-source simulation platforms provide virtual sensor models that manifest varying degrees of fidelity. Among these, CARLA [15] stands out as an open-source simulation framework offering a variety of sensor models. Another notable platform is CarMaker/TruckMaker, [16] developed by IPG Automotive, which features a specialized Simulink interface encompassing libraries for diverse sensors, including both realistic and ideal models of LiDAR and RADAR. Similarly, Vector's DYNA4 [17] provides an assortment of virtual sensor models catering to

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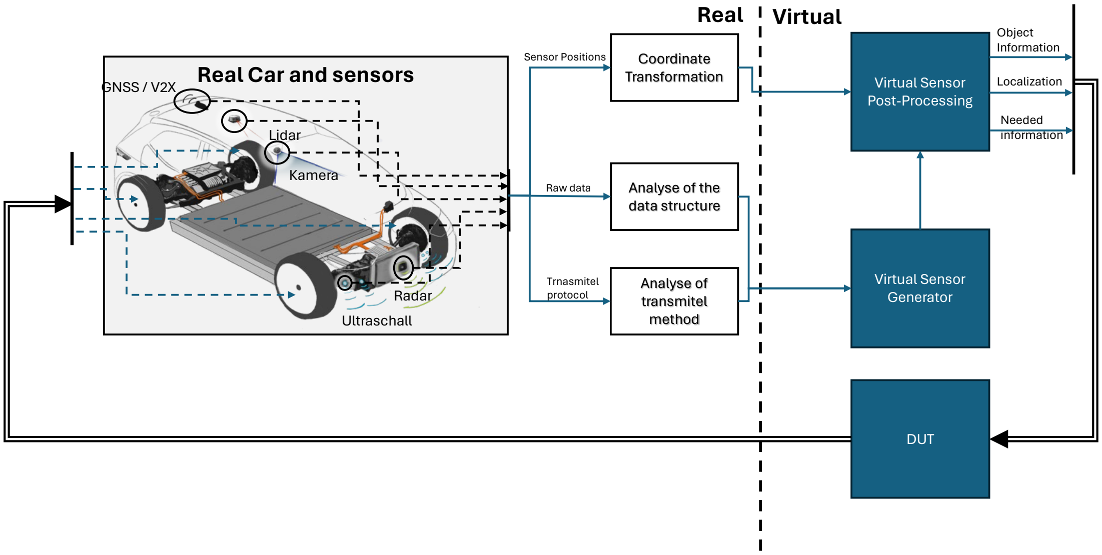

Figure 2. Concept of the sensor simulation and post-processing

LiDAR, ultrasound, and RADAR applications. Additionally, AURELION [18] by dSPACE extends its simulation capabilities by offering virtual models for LiDAR, RADAR, and camera sensors. Complementing these, the Automotive Simulation Models (ASM) models facilitate a broad spectrum of simulations, ranging from individual components like internal combustion engines or electric motors to comprehensive vehicle dynamics systems and intricate virtual traffic environments.

IV. Conception

This section presents the concept of virtual sensor simulation and post-processing. As shown in Figure 2, the system is divided into two parts: the real vehicle under test and the sensors that the vehicle has. The flowchart on the right outlines the process for simulating virtual sensors based on real sensor parameters. The process includes the following steps:

- **Analyze Data Structure**: Understand the organization, format, and internal relationships of the data.
- **Analyze Transmission Types**: Investigate how sensor data is sent, which may include communication protocols, data transfer rates, etc.
- **Coordinate Transformation**: This step converts the sensor data to a uniform coordinate system for comparison and analysis.
- **Virtual Sensor Generator**: This function block suggests a system or software to create a virtual model or representation of sensor data for manipulation or testing in a simulation.
- **Virtual Sensor Post-Processing**: After generating the virtual sensor data, this step involves further refinement or processing, which includes, among other things, feature extraction, filtering, calibration, and so on.
- **DUT**: The final block labeled "DUT" stands for Device Under Test, indicating that the processed virtual sensor data will eventually be used for testing purposes, such as testing a car's autopilot function or sensor fusion algorithms.

Where the vehicle control signals fed back from the DUT will be sent to the actual vehicle's driver, creating a closed-loop test.

V. Implementation of the Sernsor Simulation

In this section, sensor simulation as well as post-processing implementation will be carried out based on the proposed concepts.

A. Hardware introduction

This section describes the sensor data types of the real vehicle under test in terms of data transfer types and rates. Figure 3 shows the RCP function carrier AURONA. The vehicle is equipped with four direct drives and a break-by-wire system. All four wheels can be driven, braked and steered individually. GPS and LiDAR are used for position detection. Objects are detected via camera, LiDAR, ultrasound, and

Figure 3. RCP function carrier AURONA

RADAR. In this paper, we focus on the Camera, LiDAR and GNSS.

In this case, the data in LiDAR is set of laser point cloud, which can be denoted by S. Every laser point cloud $\underline{s_i}$ contains a distance value in x, y and z axis and the intense. The configurable parameters are scanning frequency f_L as well as the scanning angles θ_h and θ_v, where θ_h is the horizontal scanning angle and θ_v is the vertical angle field. Equally important is the angular resolution in the vertical $\Delta\theta_v$ and horizontal directions $\Delta\theta_h$. Using these parameters, which can be obtained from the datasheet, the P_L parameter set can be formed. The LiDAR data is transmitted via Ethernet and the actual sampling frequency is 10Hz.

The data type in the camera is a matrix $\underline{\underline{M}}$, where the size of the matrix is determined by the length l and width w of the image. For the sensor simulation, the required camera parameters are the FOV (Field of View) θ_C, the information of the lens (aperture $f_{CL}$and focal length FL_{CL}) and the frame rate f_C. All parameters of the camera can be formed as a parameter set P_C. The transmission type is Ethernet, and the frequency is 20 FPS.

The IMU and GPS sensors are integrated in the GNSS, which provide the vehicle's dynamic state$\underline{x_V}$, and absolute coordinates in the geographic coordinate system$\underline{P_V}$. The vector $\underline{x_V}$ contains the acceleration of the vehicle in the Cartesian coordinate system along the axial direction $(a_{v_x}, a_{v_y}, a_{v_z})$ and the angular velocity as it rotates around the axis of the same Cartesian coordinate system $(\omega_{v_x}, \omega_{v_y}, \omega_{v_z})$, while the GPS provides the latitude lat_v, longitude $long_v$ and altitude h_v. All parameters of the camera can be formed as a parameter set P_{GNSS}. The transmission type is CAN-BUS and the measurement frequency can reach 100Hz.

In following simulations, it’s needed to strive for the virtual sensor data to be consistent with the parameters of the real sensor data.

B. Coordinate system

In autonomous driving, the key to precise perception of the environment by the vehicle is that different sensor data can be expressed in a uniform coordinate system, so it is essential to define a uniform vehicle coordinate system and to find the position of the sensors in that vehicle coordinate. Therefore, we need to define the coordinates of the sensors as BCS_{Sensor}, and the coordinate system of the vehicle as BCS_v. The BCS_X coordinate system represents the body coordinate system. The transformation of the sensor coordinate system to the vehicle coordinate system can be expressed using the $\underline{\underline{T}}^V_{Sensor}$ matrix. The data $\underline{d_i}^{Sensor}$ in the sensor can be converted to the vehicle coordinate system by the (1).

$$\underline{d_i}^V = \underline{\underline{T}}^V_{Sensor} * \underline{d_i}^{Sensor} \quad (1)$$

C. Virtual Sensor Generator

Based on the previous state of arts, this paper describes the generation of virtual sensors using the advanced capabilities of the ASM model and AURELION. AURELION is a versatile software designed for simulating and visualizing sensor data. It facilitates the integration of actual sensor readings into various stages of development, testing, and validation processes for perception algorithms and driving functionalities. AURELION facilitates multiple development stages, such as hardware-in-the-loop (HIL) and software-in-the-loop (SIL), by providing flexible data interfaces that allow for the customization of virtual sensor parameters. Additionally, AURELION's open interface enables the retrieval and analysis of data from virtual sensors.

On the other hand, ASM offers a wide range of simulation models designed for automotive applications, which can be selectively integrated to meet specific requirements. ASM provides detailed insights into the vehicle's motion and displacement, allowing for the simulation of virtual IMU and GPS sensors. This approach, which integrates ASM and AURELION, provides a strong framework for accurately representing and analyzing vehicular dynamics and sensor systems.

D. Post -Processing

Different sensors require different post-processing methods. For camera sensors and LiDAR sensors the post-processing is feature extraction. In this work, the camera images are used to identify other traffic participants and traffic signals in the virtual environment based on the YOLO [18] algorithm. YOLO V8 is used in this article and notable for its speed and efficiency, dividing the image into a grid and simultaneously predicting bounding boxes and probabilities for each grid cell.

A key formula in YOLO calculates the confidence score for each bounding box, indicating the likelihood of object presence and the accuracy of the box location, which can be represented by the (2).

$$Conf(Obj_C) = P(Obj_c) \cdot IOU^{truth}_{pred} \quad (2)$$

Here, $P(Obj_c)$is the probability that an object exists within the box, and IOU^{truth}_{pred}represents the intersection over union between the predicted and the actual bounding boxes.

The virtual LiDAR sensor can obtain the object of the surrounding traffic participants and their location information in real time through Exwayz's [19] object recognition algorithm.

In virtual simulation, we cannot directly obtain the global coordinates under the Geographic coordinate system provided by GPS but are based on the global coordinates of the simulation environment $\underline{P_t^{VE}}$. To obtain GPS information, it is necessary to convert the coordinates in the simulation environment into GPS coordinates. Since the virtual simulation environment is built based on the real scene, the initial position of the Ego vehicle in the virtual environment can be obtained as $\underline{P_0^{VE}} = (x_0^{VE}, y_0^{VE})$, which corresponds to the GPS data $\underline{W_0} = (lat_0, long_0)$ in reality.

When the vehicle starts to move, the position of the vehicle at any moment in the virtual environment can be expressed by $\underline{P_t^{VE}} = (x_t^{VE}, y_t^{VE})$. The final GPS coordinate $\underline{W_t} = (lat_t, long_t)$ can be represented by (3) and (4).

$$lat_t = \frac{(y_t^{VE} - y_0^{VE})}{er} \cdot \frac{180}{\pi} + lat_0 \quad (3)$$

$$long_t = \frac{(x_t^{VE} - x_0^{VE})}{er \cdot \cos\left(lat_0 * \frac{180}{\pi}\right)} \cdot \frac{180}{\pi} + long_0 \quad (4)$$

Since the motion parameters of the car obtained from the simulation model are ground truth, which has no noise, while the data in the real IMU sensor includes zero-bias and random walk noise, the post-processing for the IMU sensor is to assign the motion state values to the real noise, whose noise values can be found in the manufacturer's parameter descriptions. Therefore, the simulation of real IMU values should be done by (5) and (6), where $\underline{\tilde{\omega}}$ and $\underline{\tilde{a}}$ are the noisy IMU measurement, b_g, b_a are the zero bias of the gyroscope and accelerometer, and n_g, n_a are their random walk noise.

$$\underline{\tilde{\omega}} = \underline{\omega} + b_g + n_g \quad (5)$$

$$\underline{\tilde{a}} = \underline{a} + b_a + n_a \quad (6)$$

E. Result

In this section, the results of the post-processing will be shown, as can be seen in Figure 4, where the vehicles and traffic signals at the crossroads in the image captured by the virtual camera are successfully detected, and the detected objects are boxed by the rectangular frame. After the object is recognized, its corresponding weight is displayed.

Figure 4. Object Detection in the camera image

The recognition of objects in the virtual LiDAR point cloud is illustrated in Figure 5, where the recognized objects are boxed by cubes.

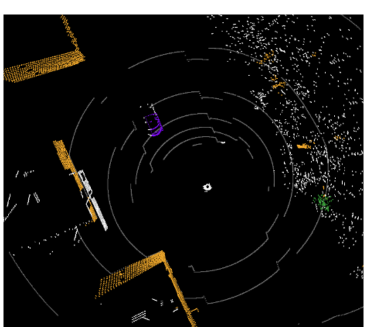
Figure 5. Object Detection in the Point-Cloud

Figure 6 and Figure 7 show the data from the virtual IMU. In order to make the noise in the IMU data more visible, a release frequency of 100 Hz (the same as the real device) was used to simulate two hours of IMU stationary. In that case, the measurements of the noiseless IMU should be 0 except for the z-axis acceleration, which receives the effect of gravitational acceleration. With the added noise, the value of this IMU is around 0 and z -axis acceleration is around the -9.81.

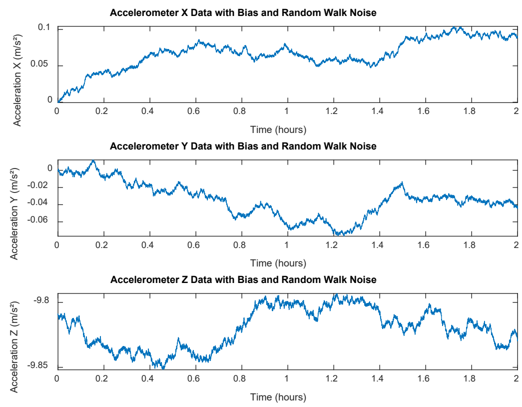

Figure 6. Noisy IMU data-acceleration

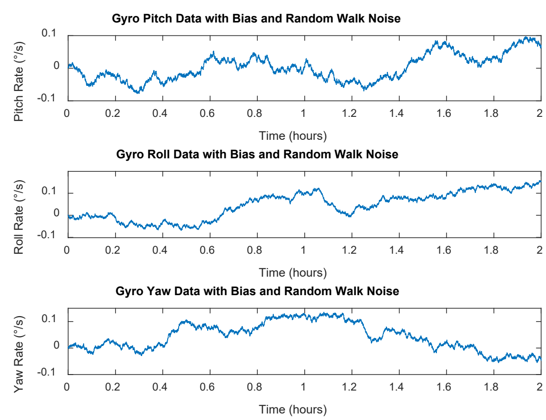

Figure 7. Noisy IMU data - angular velocity

Figure 8 shows the GPS values. Loading the converted GPS path into OpenStreetMap shows that its virtual GPS data basically matches the real driving path.

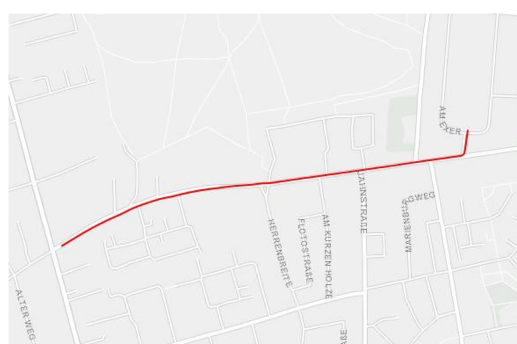
Figure 8. Simulated GPS path on the map

VI. CONCLUSION AND FUTURE WORK

This paper describes the simulation of virtual sensors in ERAGON, a highly configurable real-time test system for intelligent vehicles that simulates autonomous driving environments together with the functional vehicle AURONA. The paper focuses on camera, LiDAR, GPS and IMU sensors and post-processing techniques including feature extraction and noise modeling to refine the virtual sensor data for practical applications. The results section illustrates the effectiveness of the system in detecting vehicles and traffic signals through virtual sensor data, demonstrating the potential of virtual simulation in enhancing the design and testing of self-driving car technologies. The following work will continue to refine the techniques for virtual sensor simulation and post-processing, and fusion of multiple virtual sensors.

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