Miniature Autonomy as One Important Testing Means in the Development of Machine Learning Methods for Autonomous Driving: How ML-based Autonomous Driving could be Realized on a 1:87 Scale

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Abstract: In the current state of autonomous driving machine learning methods are dominating, especially for the environment recognition. For such solutions, the reliability and the robustness is a critical question.

A "miniature autonomy" with model vehicles at a small scale could be beneficial for different reasons. Examples are (1) the testability of dangerous and close-to-crash edge cases, (2) the possibility to test potentially dangerous concepts as end-to-end learning or combined inference and learning phases, (3) the need to optimize algorithms thoroughly, and (4) a potential reduction of test mile counts.

Presented is the motivation for miniature autonomy and a discussion of testing of machine learning methods. Finally, two currently set up platforms including one with an FPGA-based TPU for ML acceleration are described.

1 INTRODUCTION

Autonomous driving (AD) is a research topic for several decades now. The dominating methods for the subtask of environment recognition changed from classical pattern recognition to methods using machine learning (ML) and in the past years specifically to proposals based on deep learning (DL). Especially with such methods it is often not clear how robust they will work if rolled out on the streets. New solutions/methods can be tested at first in simulations and/or with recorded data, followed by first real world tests on non-public test tracks, and finally on public streets. This can be done component-wise (software, electronics, mechanical components), for a set of components, or for a whole system.

However, AD is a complex problem, especially as the environmental variations are huge. The test of new methods needs to cover a large number of different traffic situations to ensure proper functioning when brought to market. Therefore, often malfunctioning is recognized after thousands of test miles in public traffic. For a safety critical system that is not acceptable according to the relevant standards, e.g. ISO 26262. Thus, further means to ensure the overall system safety are required.

One further testing means in addition to simulations and real-world tests are tests using model vehicles. Such tests are also carried out in competitions, e.g., the Carolo Cup for vehicles on a 1:10 scale (Zug et al., 2014). We propose an even more miniaturized setup with vehicles on a scale of about 1:87. This has some advantages: One point is that at this scale there are several off-the-shelf components available for vehicles and for the environment, as it is used for model railways. Moreover, existing model railway setups can be used for testing. For example, we use the Miniatur Wunderland in Germany for tests (Wunderland, 2019). Another important advantage are the high demands of a more miniaturized vehicle: by this additional challenge not only electronics and mechanics need to be optimized but also the algorithms used for advanced driver assistance systems (ADAS) and autonomous driving (AD). Especially ML-based methods which might be used on standard PC hardware without thinking about, need to be checked carefully and revised when run on a miniature autonomy setup.

The option of using model vehicles instead of real cars or simulations gives some interesting advantages:

- First physical tests can be carried out before finishing or even starting vehicle design.
- Unusual or even dangerous i.e. close-to-crash sit-

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uations can be tested (edge cases).

- The differences between model setup and model environment on the one hand and the real vehicle, sensors, and environment on the other hand are actually not an issue. This is, because the lower level sensor processing (object detection, range measurement, etc.) needs to be tested separately, anyways. One more critical problem in many close-to-crash situations or accidents is the higher layer where, e.g., sensor readings of different modalities are fused, and/or sensor readings are interpreted. Tests of these higher levels are supposed to be performable on a miniature scale, too.
- To test ML-based solutions that combine learning and inference/recall in the application on the vehicle, miniature models are preferable. The effect of learning on a vehicle, after roll-out is hard to estimate and even if combined with additional safety means this can be a dangerous step on real vehicles.
- Finally, running many miniature model vehicles in a miniature environment 24/7 might be a means to reduce the number of test miles needed later on the real vehicles.

This paper presents first ideas for such a testing concept. The following section discusses general aspects of testing autonomous driving solutions using ML-based algorithms with regard to currently valid standards. The currently employed hardware platforms are described in section 3. Specific aspects relating to the FPGA-based ML acceleration are presented in section 4. The paper closes with considerations concerning the next steps and a short summary.

2 TESTING OF MACHINE LEARNING BASED AUTONOMOUS DRIVING METHODS

As, e.g., Koopman et al. point out "it is more important than ever to understand the gaps between theory and practice in automotive computer-based system safety" (Koopman, 2018). According to ISO 26262 (see, e.g., (Gebhardt et al., 2013)) design, verification and validation activities should relate to the Automotive Safety Integrity Level (ASIL). Typical validation acitivities comprise hardware-software integration tests, system integration tests, system tests. All of these levels need to take into account the respective functional safety requirements as well as functional correctness and general dependability requirements. Typically, test approaches include analysis techniques as well as dynamic tests. Complex systems require a well-defined test concept, which often includes Hardware-In-The-Loop (HIL) as well as Software-In-the-Loop (SIL) phases. A general decision is whether dynamic tests should be performed on the target computer or whether an emulator or simulator provides a sufficiently realistic environment for the components to be tested. The use of emulators or simulators may require additional qualification of the software tools employed. For each requirement, it needs to be decided whether the tests performed in the simulation environment need to be rerun on the final target hardware (see, e.g., (Rierson, 2013) for tool qualification in the aviation context of DO-178C). It is generally acknowledged that some types of errors can not be detected in a simulation.

For autonomous driving, the usual assumption that low-level components are individually tested, may not hold. AI-based learning methods are not suitable for traditional testing, e.g., typical requirements relating to code coverage or even requirements coverage are not easily applicable for the resulting neural networks.

Typical test approaches e.g. for obstacle detection or in general picture recognition divide the available input data into training and test sets. The training set is used to learn the respective data and the pictures from the test set are then used to validate the learning success. The data acquisition thus is a critical part for the validity of the resulting algorithm. There remains an uncertainty with regard to situations not represented in the original training or test data.

System level tests on the other hand may not be feasible in a realistic setting – i.e. on the road – due to general restrictions for non-certified vehicles. The current approach comprises prototypical situations due to driving in non-critical areas for as long as possible.

We propose a testing concept which exceeds simple simulation, but allows for a far more controlled environment configuration than the final prototype by using miniature vehicles. This test level should be additional to the usual tests of components, integration and systems tests and should focus on critical situations, which are not easily reproducible in realistic settings. Similar to the use of emulators or simulators we expect additional efforts for the validation of the miniature vehicles. The benefit for this additional effort should be a very controlled setting especially for robustness tests and fault injections, which may not be possible for the final system itself. This approach requires a thorough risk analysis approach especially for those scenarios relating to safety critical situations due to autonomous decisions. Ideally this analysis would also provide additional test cases for component tests - but this is not the primary objective.

3 MINIATURE VEHICLES

In the computer science department of HAW Hamburg various autonomous model vehicles have been developed and built for use in research and teaching in the last 10 to 15 years. In particular, students of HAW have been participating in students competition Carolo-Cup which is held each February at TU Braunschweig (see for example (Nikolov, 2009) and (Braunschweig, 2019)). Model vehicles of scale 1:10 had to be constructed for this competiton. The miniature vehicles (scale smaller than 1:10) described in this article have been developed based on the following preliminary requirements:

- explore miniaturization of autonomous systems
- develop small and cheap autonomous systems for teaching and further research
- be able to use Miniatur Wunderland Hamburg as autonomous driving test area (Wunderland, 2019)
- exploit and study miniaturization of machine learning hardware

In this article two different miniature autonomous vehicles shall be de described.

3.1 Autonomous Vehicle Type 1: Sedan Car

The type 1 vehicle is designed as a sedan car on a scale of 1:63 (see Figure 1, left). It is equipped with 2 degrees of freedom (parallelogram steering), a camera, an ESP32 micro controller board and a battery with charging circuit.

A custom design of the vehicle frame, chassis and parallel steering was made and printed out on a 3D printer. As a result, the development of a precise steering using a linear servo and a precise drive using a micro transmission was possible. This overcame the downside of electric toy cars with their for this purpose insufficient mechanics.

The current control algorithms cover lane detection, lane following, and obstacle detection in a classical, image based non-ML-based fashion. A wide angle lens for the camera is used to enlarge the visible area of the camera. Images are transformed into world coordinates using a dynamic region of interest and fixed point calculation to reduce the necessary computational power. Lane detection is performed in the transformed image using scan lines and intelligent search algorithms. Obstacle detection is included in the method. Lane following is achieved using a pure pursuit algorithm (Coulter, 1992) (Nikolov, 2009). The vehicle drives autonomously on a parcours similar to the one used at the student competition for autonomous model cars in scale 1:10 Carolo-Cup at TU Braunschweig (Braunschweig, 2019). The roadway consists of a black floor which has white road marking attached. Battery lasts for about 9 minutes.

A telemetry application has been developed which is used for easy remote access via WLAN to the vehicle. In particular this is currently used for parameter tuning and observation of the camera image.

Experiments in Miniatur Wunderland have not yet been made at this point.

In the future, image data could be collected via the telemetry application to feed off-site ML algorithms. It is planned to recall the object recognition obtained in this way on the miniature truck (vehicle type 2) which contains an FPGA-based ML acceleration for this purpose.

3.2 Autonomous Vehicle Type 2: Truck

For the computation of ML-based algorithms hardware acceleration and, thus, more space is needed. For that reason a second platform (“type 2”) is designed which corresponds to a truck with trailer on a scale of 1:87 (see Figure 1, right). Also for this platform, as testing environment the commercial 1:87 scale model railroad Miniatur Wunderland (1,490 m^2 layout size, see Figure 2) is planned to be used (Wunderland, 2019).

The “truck” platform consists of an off-the-shelf 1:87-scale truck chassis and a 3D-printed body. It will be equipped with a custom printed circuit board carrying a Xilinx Zynq 7030 FPGA. This FPGA provides enough computational power to implement machine learning methods, at least in a limited way (see section 4).

Planned sensors on the truck platform 2 are a camera, multiple distance sensors Sharp GP2Y03E and an Inertial Measurement Unit (IMU) MPU-9255. To be able to relate sensor performances on the miniature vehicle to typical sensor performances on real-world vehicles and to estimate performances on real vehicles, comparisons and calibrations are needed. For the IMU a method proposed by Tedaldi et al. is used and compared with other approaches (Tedaldi et al., 2014). The small IMU in the vehicle is compared with a XSens MTi-300 AHRS.

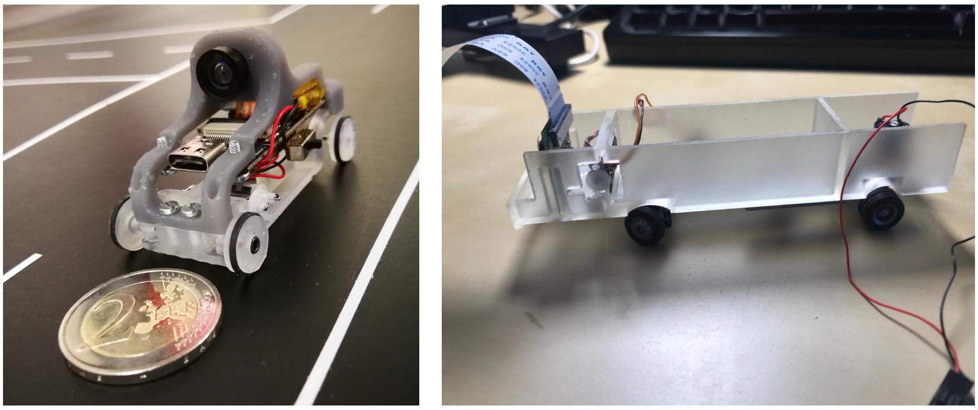

Figure 1: Left: Autonomous miniature vehicle type 1 (“sedan”, small), right: Autonomous miniature vehicle type 2 (“truck”, large). The latter is designed to carry an FPGA board while the former is controlled by an ESP32 micro controller.

Figure 2: Sample view on the Miniatur Wunderland model railroad on a scale of 1:87. Parts of the 1,490 m^2 layout could be used for tests (Wunderland, 2019; Tiedemann, 2019, under CC-BY 4.0).

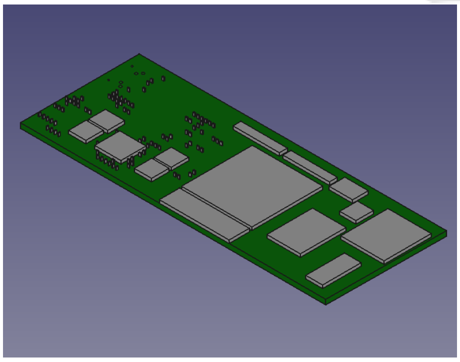

Figure 3: On the miniature “truck” vehicle a custom FPGA board with a Xilinx Zynq 7030 will be used to enable the application of ML methods on the vehicle. The board is currently planned with a size of approximately 38 mm × 84 mm. Off-the-shelf boards can not be used because of space limitations. While the first ML tests did not use FPGA-external memory (see section 4) the custom board will include DDR memory (size not fixed yet).

4 FPGA-BASED ML ACCELERATION

For the computation of ML-based algorithms on mobile compact and power critical hardware an optimized hardware design is needed. While standard micro controllers have a very low power consumption and a high single-thread performance, their computational performance on parallel/SIMD tasks like needed in machine learning is rather poor (Schenck et al., 2017). A low-power FPGA with an optimized design can lead to a much better computational performance with an acceptable power consumption.

To support different types of ML methods a general design is advantageous. One proposal was published by Google and called “Tensor Processing Unit” (TPU) (Jouppi et al., 2017). A comparable design on a Zynq FPGA was proposed by Fuhrmann (Fuhrmann, 2018) and tested on a commercial off-the-shelf board.

The test application for the first implementation was the MNIST data set of handwritten digits (LeCun et al., 1998; Lecun et al.,). The computation of small 14×14 matrices on the FPGA (without using FPGA-external memory) was about five times compared to a computation on a Intel Core i5-5287U – however, with reduced precision (Fuhrmann, 2018). If the resulting additional error is acceptable is highly dependent on the application and needs to be studied. Therefore, the next step is a test setup that uses the FPGA-based ML accelerator to classify street signs. This is the milestone for a first ML application on a 1:87 miniature vehicle.

5 CURRENT STATE AND NEXT STEPS

Currently, the sedan setup is finalized and for the truck a custom FPGA board is designed. The sensors are being calibrated, starting with the IMU and with the method proposed by Tedaldi et al. (Tedaldi et al., 2014). Figure 4 shows the IMU calibration setup including data logging system and power supply to be able to carry out different movements without the need for any external cables. For the Sharp distance sensors an evaluation with a Lidar-generated map is prepared.

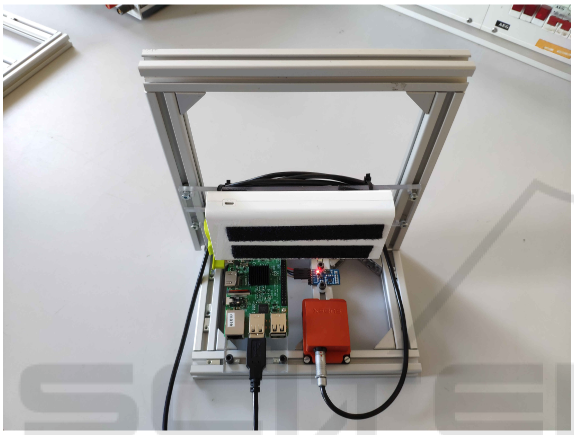

Figure 4: IMU test frame. The orange block is the XSens reference IMU, the MPU-9255 device under test IMU is mounted on the small blue printed circuit board.

When the setup has been sufficiently completed, a feasibility study for using the FPGA-based ML accelerator in combination with a vehicle is planned. This will include further considerations regarding the test of traffic sign detection both for a hard-wired net which has been trained beforehand and a version actively learning during and improving during the test phase. This phase should provide insight, e.g., in the ability of the setup to react to exceptional situations not provided during the learning phase as well as in the benefits of capturing exceptional situations during the driving phase in comparison to simulation-based generated scenarios. We assume that even in a miniature setup, e.g., the manipulation of light, contrast, partially hidden signs will be much easier than in simulations. Furtheron, we will consider if the setup allows for an automatic optimization of driving behaviour under aggrevated circumstances such as takeover or driving curves in different weather conditions.

6 CONCLUSIONS

There is indication that the use of miniature model vehicles is a helpful testing means for ML-based autonomous driving solutions – in addition to real-world tests and simulations. Using miniature model vehicles on a 1:87 scale has some specific advantages over other common scales, either directly (using off-the-shelf components) or indirectly (by the need to optimize methods thoroughly to fit to the demanding constraints).

First steps were taken to set up a fleet of miniature vehicles that could serve as testing platform for – specifically ML-based – methods to facilitate autonomous driving. Further implementation and tests will be carried out to evaluate if miniature autonomy can be realized and where it is applicable.

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