Use of Artifical Intelligence and Image Segmentation for 3-Dimensional Modeling

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Abstract. To use Augmented Reality in an automotive vehicle for testing Advanced Driver Assistance Systems a new development approach with high computing power is needed. Reasons for this are a high vehicle speed as well as fewer possible orientation points on an urban test track compared to using AR applications inside a building. With the help of Image Segmentation, Artificial Intelligence for Object Detection, and Visual Simultaneous Localization and Mapping a 3-Dimensional Model with precise information of the urban test site is to be generated. Through the use of AI and Image Segmentation, it is expected to significantly improve performance like computing speed and accuracy for AR applications in automotive vehicles.

Keywords: Artificial Intelligence, Augmented Reality, Advanced Driver Assistance Systems, Visual Simultaneous Localization and Mapping, 3-Dimensional Modeling, Image Segmentation, Object Detection

1 Introduction

Camera-based Advanced Driver Assistance Systems (ADAS) such as the active lane departure warning system and traffic sign recognition support the driver, offer comfort, and take responsibility for increasing road safety. These complex systems go through an extensive testing phase, which results in optimization potential regarding quality, reproducibility, and costs. ADAS in the future will support ever-larger proportions of driving situations in increasingly complex scenarios. Due to the increasing complexity of vehicle communication and the rising demands on these systems in terms of reliability to function safely even in a complex environment and to support the driver and increase safety, the test scenarios for ADAS are constantly further developed and adapted to higher requirements. European New Car Assessment Programme (Euro NCAP) has introduced a series of new safety tests for ADAS into its program and created a road map until the year 2025 [1] [2].

Today's test methods can be separated into two categories. On the one hand, the testing of the ADAS with the help of virtual worlds and on the other hand, the testing in reality on the test track using objects in real life. The central idea of the virtual test procedure is to transfer vehicle behavior to virtual test drives as realistically as possible. The approach for virtual tests is aimed at benefit from the advantages of simulation in terms of reproducibility, flexibility, and reduction of effort. In this way, specifications and solutions derived from them should be able to be tested and evaluated at an early stage of the development process. The use of suitable simulation methods enables the efficient design, development, and application of vehicles and vehicle components. However, virtual development methods cannot yet replace real-life driving tests in all respects. Due to the complex physical conditions in which a vehicle is transferred when testing ADAS, real-life driving tests are still necessary to the current status. For example, the weather, the surface texture of the road, and other influencing parameters take a decisive role in the evaluation process of ADAS test drives [3] [4].

The presented research background of this paper combines the advantages of ADAS-tests in a virtual simulation and these of ADAS-tests in a real environment. The camera images of the vehicle are augmented with additional virtual information. The augmentation of virtual road lanes allows, for example, the testing of a lane departure warning system independent of the test track. Scenarios such as the appearance of temporary lane markings or the absence of sections can be tested on the same test area. Narrowing and widening of lane markings can be represented as well as international differences between road markings. For testing traffic jam assistance systems, vehicles driving ahead can be augmented with camera images. In the first phase of testing, second vehicles including drivers can thus be dispensed with, reducing the costs of the tests and increasing the safety of the test engineers. Furthermore, ADAS-test cases with traffic signs as well as pedestrians and cyclists can be augmented situationally and quickly.

Furthermore, by using Augmented Reality (AR) for testing camera-based ADAS, new possibilities for testing complex, critical, and even forbidden test cases arise. For example, for testing the lane departure warning system, the traffic lane can be inserted into the image in any given width, regarding the lane and the white stripe itself. Therefore it is possible to test the system to its limits, a feature not possible by testing in reality on the test track.

For the use of AR, the system must be located (position and orientation) in its environment. This technology requires precise 3-dimensional (3D) modeling based on existing sensors. Usually, AR-applications are designed for human users and are mostly used inside buildings. Through a variety of orientation points inside a building and the movement speed of the user at walking speed, this technology is already quite advanced. The approach of this research project, by contrast, is being developed for a Electronic Control Unit (ECU), which requires a novel development approach with high computing power due to the high vehicle speed. Furthermore, compared to using AR-applications inside a building, fewer orientation points are available on a test site, so a new concept has to be developed here as well. The target of research described in this paper is to use Image Segmentation to analyze the environment of an mostly urban test site. Based on these results, a 3D model of the environment is to be created. In a further step, the 3D model is to be added by objects such as traffic signs, road markings, pedestrians, cyclists, etc. The use of Artificial Intelligence (AI) should provide precise information on the depth of the environment using 2-dimensional (2D) image sequences. Through the use of AI and Image Segmentation, it is expected to significantly improve the performance like computing speed and accuracy of the environment model. Moreover, conventional algorithms such as Simultaneous Localization and Mapping (SLAM) will be used for comparison within the research project.

Fig. 1. Augmented Reality application showing a possible scenery

The main contributions of this paper include:
1. An overview of challenges for the use of AR in the automotive vehicles with regard to camera-based ADAS.
2. An introduction of a novel approach based on visual SLAM (vSLAM) and using of AI for object identification and thus increasing the accuracy and reproducibility of ADAS in automotive vehicles.

2 Necessary Criteria for Augmented Reality

To use AR in ADAS of automotive vehicles different criteria are necessary compared to conventional AR-applications like on a smartphone. This section will describe the contrasting criteria for this approach.

2.1 Augmented Reality for Conventional Applications

According to a proposal by Azuma, Augmented Reality can be defined as a combination of three fundamental features: the combination of real and virtual worlds and precise three-dimensional registration of the real and virtual objects, both in an interactive real-time environment [5].The basic principle of AR is best known by the mobile phone game Pokémon Go, published in 2016 by Niantic [6]. Within this game, the users can interact with digital creatures through their smartphones. These creatures are placed virtually in the environment of the user. Such an AR application can be seen in Figure 1 [6]. Figure 2 shows the three parts of the algorithms behind augmented reality: image analysis, 3D modelling, and augmentation.

The image analysis serves to detect points or regions of interest within the given image. Feature detections like corner detection or edge detection are often used for this

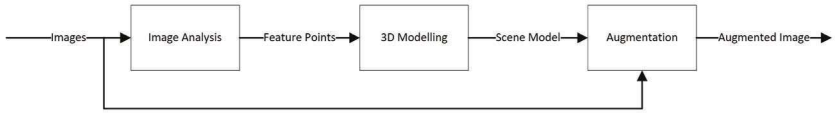

Fig. 2. Augmented Reality steps

step [7]. With the results of the image analysis, a three-dimensional model of the environment is created. The kinds of algorithms used for this step vary depending on the type of AR application. For AR in unknown locations, simultaneous localization and mapping (SLAM) or structure from motion (SfM) algorithms are widely spread [8]. The augmentation is based on the results of the 3D modelling. The scene model is usually provided as a positional description of a plane or a coordinate system representing the real world [9]. With this information, a virtual object can be placed upon the plane or in the coordinate system with adequate characteristics such as size and orientation. After the object placement, virtual content is combined with the real-world image [10].

There are several publications of applications for AR. These applications vary heavily in their fields, from the usage of AR in psychology [11] to the use in operating rooms in hospitals [12] to mobile games [6] to military applications [13]. What all these applications have in common is that the reality of a human is augmented. With the human as the user of AR, there are some implicit consequences for the application. One of them is that the human user is, in most cases, lenient towards virtual objects not placed precisely within a small range of error. Furthermore, the velocity of human movement and therefore the distance travelled by any given time is limited. By these restrictions, the requirements for localization, mapping, object placement, and runtime are not as high as in an automotive environment, as is discussed in the next chapter.

2.2 Augmented Reality for Advanced Driver Assistance Systems (ADAS) in Automotive Vehicles

For the use of AR in automotive vehicles and the associated specific use of ADAS-sensor technology on conventional test tracks, special criteria are to consider. For instance, the test sites are located outside of buildings and are usually therefore low textured [14]. In addition, there are quick scene changes due to the speed of the automotive vehicle. These points lead to the fact that conventional AR-SLAM approaches cannot perform the necessary localization- and mapping-process for SLAM-Algorithm (a reference to section 3) with the desired accuracy and resolution. Due to the desired integration of the presented approach into a serial automotive vehicle without any additional sensor technology, the aim is to generate information about the depth and texturing of the environment based solely on the installed camera. This camera is usually a mono-view-camera system that is often integrated into the rear view mirror of the automotive vehicle. Mono-view-camera systems are established vehicle hardware, which is mostly used in low-priced series models due to their compact design, high resolution, robustness, long-range and low cost. On the other hand, high-priced vehicles use stereo-view-camera systems, which enable spatial vision like a human [15].

In addition to the low textured environment of the test track and the fast change of scenery, other aspects such as weather influences like rain and the sun position, soiling of the windshield, bumps of the road surface and the lack of road markings have to be considered [16]. Furthermore, when augmented reality is used in automotive vehicles, the end-user is not the human driver, but an ECU. This implies that very high accuracy and a high realism, e.g. correct shadowing and occlusion of the augmented objects are required in the overall process [17]. In comparison to a human driver, the ECU must not detect any difference between reality and the augmented reality, otherwise, the ECU will be transferred to an error state. It is also highly relevant to consider the constant further development of ADAS, which persistently demands increased requirements for realistic test scenarios. This approach aims to achieve the same driving behavior as in reality.

In addition to accuracy, the runtime of the overall algorithm is also of great importance. Nowadays camera systems work with a frame rate of 30 to 60 Frames per Seconds [fps]. The resulting maximum overall runtime for handling one frame can be found in Table 1.

Framerate	**Maximum runtime**
10 fps	$\frac{1}{10}\,s = 0.1000\,s$
30 fps	$\frac{1}{30}\,s = 0.0333\,s$
40 fps	$\frac{1}{40}\,s = 0.0250\,s$
45 fps	$\frac{1}{45}\,s = 0.0222\,s$
50 fps	$\frac{1}{50}\,s = 0.0200\,s$
60 fps	$\frac{1}{60}\,s = 0.0167\,s$

Table 1. Several Framerate and the according maximum runtime.

For a successful evaluation of ADAS-test scenarios, the AR system must be able to orient itself in the environment very accurately [18]. One cause is the missing feedback about the impact intensity of test dummies when crashing them. For this reason, it is necessary to know the exact position of the car on the test track to calculate the intensity of the impact based on the braking distance. When using Euro NCAP test scenarios, velocities up to

$$130\,\frac{km}{h} \widehat{=} 36.111\,\frac{m}{s} \tag{1}$$

are tested. The AR algorithm must have a faster runtime compared to the speed of the camera system. The distance d the vehicle covers within a frame at any given velocity and framerate can be calculated by:

$$d = \frac{v_{Vehicle}\,[\frac{m}{s}]}{Framerate\,[\frac{frames}{s}]} \tag{2}$$

At a speed of $130\,\frac{km}{h}$ and a camera framerate of 30 fps, the vehicle travels

$$d = \frac{36.111\,[\frac{m}{s}]}{30\,[\frac{frames}{s}]} = 1.204\,\frac{m}{frame}. \tag{3}$$

Accordingly, for a framerate of 60 fps at the same speed, a distance of

$$d = \frac{36.111\,[\frac{m}{s}]}{60\,[\frac{frames}{s}]} = 0.602\,\frac{m}{frame} \tag{4}$$

is covered. A deceleration of one frame means a deviation of the test results of 0.602 to 1.204 meters.

Based on the high speed of the car and the camera, and the high need for precision in object placement, it is clear that the requirements for this application of Augmented Reality are far more strict than for the usual application for human users.

3 Development Approach

Simultaneous Localization and Mapping (SLAM) is a method for obtaining the 3D structure of an unknown environment and sensor motion in the environment. This system was initially intended to achieve autonomous control of robots [19]. Due to continuous development, SLAM-based applications have also found their way into mobile device applications and self-driving cars. To increase the accuracy of SLAM algorithms, various approaches allow the integration of different sensors, such as laser range sensors, rotary encoders, inertial sensors, Global Position Systems (GPS), and cameras. These algorithms are summarized in the following papers [20] [21] [22] [23]. Since cameras primarily are used for the most part in automotive vehicles, the approach presented in this paper is based on a subcategory of SLAM algorithms - visual Simultaneous Localization and Mapping (vSLAM). In the following section, the State of the Art for vSLAM-techniques are described. Based on these methods a new approach for AR using SLAM in automotive vehicles is presented.

3.1 State of the Art - Visual Simultaneous Localization and Mapping (vSLAM)

The approach of vSLAM uses only visual inputs to perform localisation and mapping. This means that no vehicle sensors other than the vehicles camera system are needed to create a 3D model of the environment thus making this approach more flexible than LIDARS, Radars, and Ultrasonics. The framework of vSLAM-algorithm is mainly composed of three basic modules: Initialization, Tracking, Mapping, and two additional modules: Relocalization and Global Map Optimization (including Loop Closing) [24].

Basic modules:

1. Initialization: To use vSLAM, the fundamental step is to define a specific coordinate system for camera position estimation and 3D reconstruction in an unknown environment. Therefore, the global coordinate system should be defined first during initialization. A part of the environment is therefore reconstructed as an initial map in the global coordinate system [24].
2. Tracking: After the initialization process, tracking and mapping are performed. Tracking involves following the reconstructed map in the image to continuously estimate the camera position of the image to the map. For this purpose, distinctive matches between the captured image and the created map are first determined by feature matching or feature tracking in the image [24].

3. Mapping: The mapping process expands the map by understanding and calculating the 3D structure of an environment when the camera detects unknown regions where mapping has not been done before [24].

Additional modules:

4. Relocalization: When tracking has failed, Relocalization is required. Reasons for this can be, among others, fast camera movements. In this case, relocalization makes it possible to recompute the current camera position about the reconstructed map [24].

5. Global Map Optimization (including Loop Closing): The map usually contains a cumulative estimation error corresponding to the distance of the camera movement. To eliminate this error, Global Map Optimization is usually performed. In this method, the map is refined considering the consistency of the whole map information. If previously recorded map elements are recognized, loops are closed and the cumulative estimation error can be corrected from the beginning to the present. Loop Closing is a method for obtaining reference information. While closing loops, a closed loop is first searched by comparing a current image with previously acquired images. Generally, relocalization is used to recover the camera position and loop detection is used to obtain a geometrically consistent map. Pose Graph Optimization is widely used to suppress the cumulative error by optimizing the camera positions. Bundle Adjustment (BA) is also used to minimize the map reprojection error by optimizing the map and the camera positions. In large environments, this optimization method is used to efficiently minimize estimation errors. In small environments, BA can be performed without loop closure as the cumulative error is small [24].

For the use of SLAM in automotive vehicles and the associated properties such as fast scene changes and low texturing of the environment, various approaches are available using vSLAM-Algorithm, which can be found in [14]. In this paper, different SLAM approaches are compared based on accuracy and robustness, among others. Some other approaches, which are not compared in [14] but seem promising for the presented approach in this paper, are briefly described in the following:

ORB-SLAM:

The ORB-SLAM algorithm was first presented in 2015 and seems to be the current state of the art as it has higher accuracy than comparable SLAM algorithms [25]. Here, ORB-SLAM represents a complete SLAM system for monocular, stereo, and RGB-D cameras. The system operates in real-time and achieves remarkable results in terms of accuracy and robustness in a variety of different environments. ORB-SLAM is used for indoor sequences, drones, and cars driving through a city. The ORB-SLAM consists of three main parallel threads: Tracking, Local Mapping, and Loop Closing. A fourth thread can be created to execute the BA after a closed loop. This algorithm is a feature-based approach, which represents the detected points in a three-dimensional MapPoint [14]. Figure 3 shows a MapPoint, which is created using image sequences captured in-house. The MapPoint shows a recognized house in an urban environment using ORB2-SLAM. Various advancements and improvements in terms of accuracy, robustness, etc. can be found in further developments based on this approach of ORB-SLAM (ORB2-SLAM [18] and ORB3-SLAM [14]). While the performance of ORB-SLAM is impressive in well-structured sequences, error conditions can occur in poorly structured sequences or when feature points temporarily disappear, e.g., due to motion blur [26].

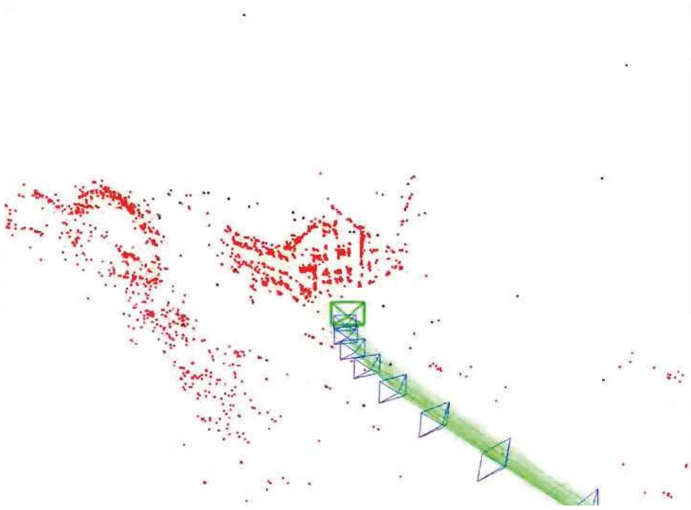

Fig. 3. MapPoint with red dots and green line for trajectory based on ORB2 with own image material in an urban environment

DS-SLAM:

ORB-SLAM exhibits excellent performance in most practical situations. However, some problems are not solved by the ORB-SLAM. First, the ORB-SLAM algorithm exhibits weaknesses in exceptionally dynamic and harsh environments. On the other hand, the map model created is based on geometric information like the MapPoint in Figure 3. This MapPoint does not provide a higher-level understanding of the environment. The DS-SLAM approach, firstly presented in 2018, combines the ORB-SLAM with the Semantic Segmentation approach using artificial intelligence to achieve a higher-level understanding of the environment. This approach further intends to increase the robustness of the SLAM system in dynamic environments. Based on ORB2-SLAM the DS-SLAM consists of basic SLAM-Modules like Tracking, Mapping, and Loop-Closing. Furthermore, DS-SLAM has two additional threads like Sementic Segmentation and Dense Map Creation. Using these additional threads improves the localization and mapping concerning robustness and accuracy in dynamic scenarios [26].

PL-SLAM:

Another approach to increase accuracy in poorly textured environments is PL-SLAM (Point and Line Simultaneous Localisation and Mapping), firstly presented in 2017. PL-SLAM extends the point-based approach known from ORB-SLAM with a line-based method. This line-based approach enables an improvement in terms of occlusions and false detections. Besides the improvement in poorly textured environments, this approach also shows increased performance in very well-textured environments, without significantly degrading the efficiency of this algorithm. Like the ORB-SLAM algorithm, the PL-SLAM has the basic SLAM modules for initialization, tracking, mapping, and loop closing. The extension of this approach is to use line-based algorithms in parallel with the point-based algorithms in each SLAM module. This approach ensures that the resulting map is more valuable and more diverse in 3D elements to derive important higher-level scene structures such as planes, voids, ground surfaces, etc. [27].

Based on the presented approaches in this section, in a further step single features of these SLAM-Algorithm are to extend and insert in a new approach for testing of ADAS in automotive vehicles. An introduction for the next steps is presented in the following section.

3.2 Use of Object Detection and vSLAM for AR in Automotive

For the use of AR in automotive vehicles, the approach should consist of using a state-of-the-art method and extending the feature point detection with an object detection. This should improve the following criteria:

- Robustness against blurred effects.
- Increase the accuracy of the 3D environment through improved depth information.
- Detect occlusions and improve 3D environment detail.
- Achieve robustness against weather effects.
- Increase realism for the control unit as end device.
- Increase computational speed with improved accuracy.
- Achieve higher-level understanding of the environment.

To achieve these criteria, the following features are to be extracted from the vSLAM approaches presented and examined in more detail for further research investigations:

ORB-SLAM:

- State-of-the-Art method to generating a MapPoint.
- Feature-Point approach should represent the basic framework.
- Selection of which criteria can be used from ORB or the further developments ORB2 and ORB3 based on it.

DS-SLAM:

- Approach of AI and Image Segmentation to generate an Object Detection.
- Creation of a Dense-Map for overlay on MapPoint.
- Achieve a higher-level understanding of the environment.

PL-SLAM:

- Based on edges to improve occlusions and improve object detection.
- Better 3D-reconstruction of objects through the detection of edges, points and lines.
- Improved realism through correct lighting and shadowing of augmented objects.

By cleverly combining the individual elements of the previously known SLAM algorithms, augmented reality in automobiles could be used in high-speed ADAS tests. In addition to the increased computing speed, increased accuracy should be achieved to be able to

Fig. 4. Top: Original Image in an Urban Environment;
bottom left: Feature-Point-Detection using ORB2-SLAM-Algorithm;
bottom right: Object Detection using Image Segmentation

make a meaningful assessment of the performance of the ADAS tests. Figure 4 shows the original image, the feature point detection of the ORB2 algorithm, and the image segmentation used so far for object detection. The next step is to combine these approaches using AI.

4 Conclusion

In this paper, we have proposed an approach to use Augmented Reality in automotive vehicles. We modeled the problem of creating an urban environment to use AR for testing in high-speed ADAS. Our approach is based on a combination of vSLAM-Algorithms like ORB-SLAM, DS-SLAM, and PL-SLAM within the combination of Artificial Intelligence to use Object Detection. This should help to generate a better overall performance concerning computing speed and accuracy.

The creation of a virtual 3D environment with a superior understanding of the individual objects should, in a further step, make it possible to augment other sensors such as the car's radar and lidar with objects in addition to the camera data. This should once again increase the overall performance of the entire system.

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