# "Pedestrian in the Loop": An approach using virtual reality

Michael Hartmann*†, Marco Viehweger‡, Wim Desmet‡, Michael Stolz*, Daniel Watzenig*
*University of Technology Graz and Virtual Vehicle Research Center, Austria
{michael.hartmann, michael.stolz, daniel.watzenig}@v2c2.at
‡KU Leuven and Member of Flanders Make, Belgium
{marco.viehweger, wim.desmet}@kuleuven.be
†University of Liverpool, United Kingdom
{michael.hartmann}@liverpool.ac.uk

***Abstract*—A large number of testing procedures have been developed to ensure vehicle safety in common and extreme driving situations. However, these conventional testing procedures are insufficient for testing autonomous vehicles. They have to handle unexpected scenarios with the same or less risk a human driver would take. Currently, safety related systems are not adequately tested, e.g. in collision avoidance scenarios with pedestrians. Examples are the change of pedestrian behaviour caused by interaction, environmental influences and personal aspects, which cannot be tested in real environments. It is proposed to use Virtual Reality techniques. This method can be seen as a new *Pedestrian in the Loop* testing procedure.**

***Index Terms*—Autonomous vehicles, Advanced driver assistance systems, Collision avoidance, Vehicle testing, Virtual reality, Testing with pedestrians**

## I. Introduction

Testing of autonomous vehicles for complex and uncertain environments has become one of the biggest challenges in the automotive industry. Automation and computational intelligence will increase abilities of the vehicle [1]. The environment perception and situation understanding will be covered, by computer algorithms. In addition to vehicle dynamics, the environmental states have to be incorporated into the test [2]. In order to ensure safety, it is required to test the intelligent vehicle in a reasonable way. It is also necessary to have prediction mechanisms to infer the consequences of decisions correctly. Conventional testing procedures are insufficient to ensure safety of increasingly complex future assistance functions involving machine perception and cognition [3]. The paper is structured as follows: The first chapter introduces testing for safety related systems. In the second chapter the state of the art of test environments is summarized and the third chapter rates their use in situations with pedestrians. In chapter four solutions are proposed and finally some conclusions for this new test environment are discussed.

### A. Compromise in risk taking

The vehicle has to find in each situation a reasonable trade-off between safety and efficiency, which can lead to different levels of risk taking especially in motion planning. In classical driving situations a driver perceives the environment through to his sense organs, thinks and decides consciously or unconsciously about the next suitable driving manoeuvre. The same is true for a pedestrian, where the dynamics is different. The ability of pattern recognition helps to decode the causality of the situation and enables to infer future situations and reason about the consequences of the (planned) action [4]. More experienced and talented drivers can take more risky manoeuvres than untalented drivers. With higher risks, the probability for collisions will increase. The driver nevertheless has a responsibility within his decision making, which has to be translated into a machine understandable language. Fig. 1 shows aspects of a reasonable trade-off in risk taking influenced by society, environment and vehicle. Safety generally has a higher priority than traffic flow, but it is also expected that the vehicle does not hinder other road users. Risk depends also on which kind of driving manoeuvres are authorized or restricted. The perception and cognition of the environment and the trust in correctness of the perceived information is also decisive. Whether the environment is structured or unstructured, simple or complicated, changes the scope for action. Urban environments are often more complicated than highways. With the total knowledge about

| | **Aspects in influencing risk** | | |
|---|---|---|---|
| **Society** | Safety | | Traffic Flow |
| | Authorization | | Restriction |
| **Environment** | Structured | | Unstructured |
| | Simple | | Complicated |
| | Knowledge/ Determinism | | Uncertainty |
| | Belief | Lack of knowledge | Dis-Belief |
| | Most probable single belief | | Multimodal beliefs |
| **Vehicle** | Control | | Loss of control |
| | Deterministic and known system behaviour | | Variable and uncertain system behaviour |

Fig. 1. Aspects for a compromise in risk taking for motion planning of (autonomous) vehicles

a new situation and resulting determinism, the consequences and risk of a (planned) action can be inferred. This is not the case if the situation is uncertain. This kind of predictive sensing of the future can be distinguished by the type of information about a certain event. The (un-)certainty about a future event can be modelled as belief or disbelief [5]. The belief or disbelief that a perceived pedestrian will cross the street can be modelled by classical probabilistic forms. In each situation there exists always a lack of knowledge, e.g. the future intention of the pedestrian. The lack of knowledge leads to several plausible possibilities where the pedestrian can move in the future. Situation prediction can be divided in the most probable belief or different possible future beliefs (multimodal beliefs) [4].

The control or loss of control of the vehicle depends on the environment, the modelled system dynamics (e.g. linearity/nonlinearity), the control architecture, the proper functioning of the whole system (e.g. electronic devices) and external influences (e.g. weather, road conditions). The system behaviour (e.g. vehicle dynamics) can be divided in known and deterministic or variable and uncertain behaviour. Overall, this kind of aspects will lead to certain degrees of confidence about the future situation, the acceptance of lack of knowledge (compare e.g. Dempster Shafer rule in [5]) and a variable assessment of risk.

### B. *Need for testing new functionality*

Aim of an autonomous vehicle is to show a superior performance over an average driver with respect to persons injured. By statistical considerations, a highway assistant should be tested on a reference route of 240 million km [6]. In practice this is not feasible. Another problem is the assessment of driving performance using simple metrics. The selection of such metrics is not straightforward [6]. The complexity of tests for autonomous vehicles is much higher, compared with conventional test procedures. Additional to vehicle states, information of the environment is incorporated in the decision making process of an autonomous vehicle. This leads to an increase of complexity, also because of predictions. The possibility to miss important and risky trajectories is the major safety risk [7]. Although no error could be detected in a test-run, it does not mean that there has not been an error, good conditions of the environment could have masked the error. Also the analysis of failed tests is not trivial. To find error causes (e.g. why there has been a collision) in data is a problem, due to the complexity of driving situations and unknown causal chains. Reproducibility of test cases and adequate representation forms of complex situations (e.g. semantic representation) are further aspects.

General requirements of test procedures for autonomous vehicles include:

- Clear and reproducible statements;
- As easy as possible, as complex as necessary;
- Possible and adequate for all environments and situations [1];
- Meaningful metrics (e.g. measures for the safety-risk-ratio) and suitable description forms;
- Measures for robustness and redundancy for safety reasons;
- Adequate for testing realistic driving scenarios [8];
- Comparison to human performance [9];

## II. State of the Art

This chapter starts with a section II-A about the historical development of vehicles and continues with some test procedures and test environments (section II-B). Existing test environments are analysed for the use in automated driving situations (section II-C).

### A. *Historical development of vehicles*

In Fig. 2 the historical development[1] of vehicles is shown simplified in four stages and six categories based on [3]. In the first period, vehicles were just deterministic machines, controlled by human drivers without any algorithmic environment recognition aiming at a stable reaction to the driver control and only vehicle states were measured by sensor types like odometry and inertial sensors. This kind of proprioceptive sensing was extended to exteroceptive sensing [3], where details from the surrounding environment were detected. The idea was to build systems which inform, warn or increase the comfort for the driver.

In the last decade it became possible to drive with autonomous vehicles in simple structured environments[2]. In many cases stochastic concepts for representing uncertainty (lack of knowledge) were used. In complex situations there are a lot more concepts necessary for safety of autonomous vehicles in environments with pedestrians. Urban environments have a very complex causal structure. Decoding the causal structure and its effects is relevant for situation prediction. Also the future intention of the pedestrian cannot be directly inferred by analysing the position, gesture and social environment. The causality of a new situation has to be safely decoded [4] in combination with concepts for uncertainty quantification [5] to increase vehicle safety. A pedestrian is a social subject, where environmental influences, the urban development, culture and interactions will also influence the behaviour of the pedestrian. In many cases infrastructural information and biomechanics have to be incorporated. To reach an even better risk compromise, the environment perception with onboard-sensors needs to be complemented by network perception systems.

### B. *Test methods and environments*

Testing safety of dynamic systems can be divided in different strategies [7]. To classify a system as a safe system, it is necessary to make sure that trajectories never reach unsafe states.

[1]In the context of environmental understanding and decision-making

[2]In [10] autonomous vehicles are classified in four levels depending on the degree of autonomy

| Goals | Vehicle Dynamics | Information, Warning & Comfort | Automated & Cooperative Driving for simple environments | Automated & Cooperative Driving for complex environments |
|---|---|---|---|---|
| **Environment Recognition** | ---- | Surrounding environment | Structured environment | Complex structured urban environment |
| **Concepts** | Determinism | Determinism | Stochasticity | Uncertainty Quantification, Causality, Urban development and culture, Geo-Science, Biomechanics… |
| **Functions** | Stabilization | Information, Warning & Comfort | Move independently | Move independently |
| **Perception** | Vehicle States | Signal-, Feature-, Object-Level | Environment with low complexity | Environment with high complexity, Network perception |
| **Sensors** | Odometry, Inertial Sensors | Ultrasonic, Radar, Infrared sensor, Lidar, Vision | Sensor Network: Multi-sensor, Traffic Sensor | Sensor Network: Cloud Services, Networked systems |
| **Examples** | ABS, ESC… | Lane Departure Warning, Park Assist… | Collision Avoidance, Automated Driving on highway | Collision Avoidance, Automated Driving in urban environments with pedestrians |

Fig. 2. Evolution of vehicles (expanded from [3])

The validation of technical systems is often done by simulation and experiments. If the trajectory hits the unsafe state during a simulation, the system can be declared an unsafe dynamical system. As long as a counterexample has not been found, there is no direct way to declare the system safe. There are some exploring techniques for the state space to find the counterexample systematically [7].

In conventional driving tests (e.g. testing vehicle dynamics), internal vehicle states have to be examined at specified manoeuvres. For autonomous driving functions, there are no standardized tests, because states of the environment are essential. It is not trivial to determine the external states and conditions that have to be used for tests in order to ensure a clear statement for the safety of the vehicle. Also, due to the diversity of situations, the number of tests for demonstrating safety is tremendous.

For the reproducibility of real-world tests, some strategies are known. Steering robots are already used in experimental settings. Another strategy is to collect a large amount of data during long-term studies to ensure that the system is tested for all possible situations [6]. Hereby the problem of missing trajectories plays an essential role.

Soft-crash-targets and passable target robots can be used to model accident scenarios. These crash target robots are already used because they can be precisely coordinated [6].

The decision making process is influenced by the interaction with other road users. The intention estimation and the prediction for the future movement of road users is vital for the motion planning of the ego-vehicle [2].

### *C. Existing test environments and their applicability to autonomous vehicles*

Existing test environments are analysed for the usage in automated and cooperative driving scenarios (Fig. 3). They can be classified as indoor, outdoor and virtual test environments. A separate class is used, which is not directly a new test environment, to accentuate the existence of tests with special test equipment. Indoor tests [12] enable specific environment conditions, where pedestrians or real complex environments cannot be incorporated. Therefore, models have to be created, which represent the main aspects of the real behaviour of pedestrians and environments. The same applies for virtual environments, where virtual models are used in a specific software language. A special environment with use of augmented reality to test the driver performance is presented in [13]. Outdoor experiments have often the same problem of simplifying the reality to certain expressions and levels. This leads to lack of generalizability. For safety reasons, real pedestrians and complex urban environments are often incorporated only after a large amount of tests in other test environments (e.g. long-term study). The type of experiments with real pedestrians are more observational studies rather than randomized controlled experiments. It is important to test interaction, perception, environmental influences and external interventions [4], [14].

## III. Problem description

In this chapter the challenges in predicting and testing safety critical situations with pedestrians are discussed. In section III-A influences on the human behaviour are analysed. In section III-B important test criteria are discussed and a

| | | Aim | Automated & Cooperative Driving for simple structured environments | Automated & Cooperative Driving for complex environments |
|---|---|---|---|---|
| Indoor | Tests in specialized test facilities/ Experimental plant (e.g. HIL, SIL, MIL, VIL) | Test a partial aspect (e.g. Software module, Hardware, overall performance, variability) | With models it is possible to replace pedestrians | |
| | Driving simulator | Incorporating a driver | Depending on the level 1-3 of autonomous vehicles, where the driver responsibility in steering and monitoring of the environment can be tested | |
| | Indoor testbeds with robots | Small-scale test under favorable conditions for visualization and feasibility analysis | Represent pedestrian behavior by robots and collision avoidance under simplistic environment conditions | |
| Outdoor | Test drive | Short-term study | For safety aspects it is not possible to test with real pedestrians (therefore experiments with robots are used) | |
| | Experiments with robots | Substitution for real pedestrians (e.g. movement behavior with(out) biomechanics) | Predefined trajectories of pedestrians in collision avoidance (without) incorporating the biomechanics of pedestrians | |
| | Long-term study | Long-term study | Long-Term study without interaction of highly dynamic road users (e.g. pedestrians) | Random interaction with pedestrians |
| | Tests in specialized infrastructure | Incorporating an infrastructure (e.g. Car2X) | Incorporating of sensors in simple structured environments (e.g. highway) | Incorporating of sensors in urban environments |
| Other | Tests with special equipment | Depending on the sensors and algorithms (e.g. eye capture, algorithms for recognition of driver tiredness, steering robot) | Special cases (e.g. driver behavior in collision avoidance, special maneuvers) | |
| Virtual | Virtual Validation | Virtualization of the environment | Pedestrian movement some with incorporating the bio-mechanics without incorporating pedestrians | Need for interventional testing, incorporating the biomechanics and psychological testing (e.g. Causal Inference) |

Fig. 3. Qualitative analysis of test environments for automated driving in simple and complex structured environments (based on [2], [6], [1], [9], [4], [11])

selection of these test criteria are used to rate existing test environments for the use in test scenarios with pedestrians.

### A. *Influences of human behaviour*

Influences on the algorithmic understanding of human behaviour are summarized in six different groups (Fig. 4). The human behaviour is influenced by the environment. For ensuring the safety of autonomous vehicles it is necessary to test the algorithms of autonomous vehicles especially in complex and uncertain environments with pedestrians. The causality of each situation should be decoded to detect intention-changes and influences of external interventions. Uncertainty is inherent in every situation, that is why no absolute certainty is ensured in each movement prediction. Some of the authors of this contribution proposed to distinguish between epistemic and aleatory uncertainty [15]. If the position of a pedestrian is measured, the epistemic uncertainty for the future predicted movement can be reduced with more measurements, but there exists a non-reducible uncertainty (aleatory uncertainty). On the other hand there is a certain amount of determinism in human behaviour, which can be employed for movement prediction. The bio-mechanics and also the environment (e.g. perception and physical constraints by walls and rivers) of a pedestrian constrain the dynamics. A lower dimensional dataset can be representative for the human movement comparing to the number of joint angles of a human body (high-dimensional dataset) [16]. Also statistically repeated patterns (e.g. habits) can be usable for developing algorithms for describing the behaviour (e.g. movement prediction). Each person is unique. Depending on the knowledge there is a fluent crossing between determinism and uncertainty. Psychological aspects, unexpected happenings and events, and changes of perception lead to change in behaviour.

### B. *Evaluation for test environments with criteria in collision avoidance scenarios*

Some decisive criteria for testing collision avoidance algorithms with pedestrians are illustrated in the category columns of Fig. 5. The environment complexity is one of the most important aspects, where the interaction between road users, the perception, the motion, and environmental influences have to be tested. To check the generality of real-world test cases with pedestrians it is necessary to recreate real world scenarios and repeat each experiment. A classification in representative target groups might be advantageous.

| Environment | Complexity | Causality | Uncertainty | Determinism | Personality |
|---|---|---|---|---|---|
| • Environmental understanding (e.g. urban scenarios)<br>• Cultural Developments and events<br>• Static, (quasi-)static and dynamic obstacles<br>• Spatial- and Time-Dependencies | • Human movement perception<br>• Multimodality in prediction<br>• Mathematical formalism | • Intention-Change<br>• External Interventions<br>• Causal-chains | • Knowledge, free will and mind<br>• No absolute certainty<br>• Epistemic and Aleatory Uncertainty | • Biomechanics<br>• Statistical repeated patterns (e.g. habits) | • Determinism and uncertainty (dependent on knowledge)<br>• Age, gender, nationality, culture<br>• Psychological aspects (e.g. mood, quickness of action)<br>• Reaction to external influences<br>• Perception and room for maneuver/freedom to act |

Fig. 4. Influences on human movement (based on [4], [5], [11])

<table>
<tr><th></th><th></th><th colspan="3">Testing</th><th colspan="3">Generalizability of tests</th></tr>
<tr><th></th><th></th><th>Interaction</th><th>Changeability of the environment</th><th>Recreation of real world scenarios</th><th>Repeatability of the experiment</th><th>Test of safety-critical system (i.e. collision avoidance)</th><th>Safety requirements</th></tr>
<tr><td></td><td>Explanation</td><td>Interaction between vehicle and pedestrian</td><td>Test in changing environments</td><td>Ease of changing the environment</td><td>Same results for two identical test set-ups</td><td>Test of a safety critical system with pedestrians</td><td>Safety requirements (i.e. vehicle dynamics, organizational requirements)</td></tr>
<tr><td rowspan="3">Indoor</td><td>Tests in specialized test facilities/ Experimental plant (e.g. HIL, SIL, MIL, VIL)</td><td rowspan="5">Models for pedestrians</td><td colspan="2" rowspan="2">Models</td><td>Often adequate</td><td rowspan="3">Not possible (i.e. safety reasons)</td><td rowspan="3">Often adequate</td></tr>
<tr><td>Driving simulator</td><td rowspan="4">With variations</td></tr>
<tr><td>Indoor testbeds with robots</td><td colspan="2">Models</td></tr>
<tr><td rowspan="4">Outdoor</td><td>Test drive</td><td rowspan="2">High expenses</td><td>Environment dependent</td><td rowspan="4">Safety problem</td><td rowspan="4">High requirements</td></tr>
<tr><td>Experiments with robots</td><td>Models</td></tr>
<tr><td>Long-term study</td><td>Random appearance of pedestrians</td><td>Not adequate</td><td rowspan="2">Environment dependent</td><td>Random</td></tr>
<tr><td>Tests in specialized infrastructure</td><td rowspan="2">Models for pedestrians</td><td>High expenses</td><td>With variations</td></tr>
<tr><td>Virtual</td><td>Virtual Validation</td><td colspan="2">Virtual models</td><td>Often adequate</td><td>Not possible (i.e. safety reasons)</td><td>Often adequate</td></tr>
</table>

Fig. 5. Qualitative evaluation of existing test methods with selection of important criteria (based on [2], [6], [1], [9], [4], [11], [12])

Fig. 5 summarizes a qualitative evaluation of existing test methods with important criteria. In all test environments, besides real traffic tests, there are models for the representation of human behaviour. The movement of pedestrians is mostly pre-programmed and describable by fixed trajectories. Stochastic models and interaction, environmental influences, and personal aspects are not tested. There exists often no pedestrian perception stimuli unit. Exceptions are long-term studies, where pedestrians appear randomly and the type of experiment is observation inspired [17].

## IV. Proposed solutions

From chapter III following facts are revisited to propose a new test concept:

- There is no absolute certainty in pedestrian movement prediction due to a lack of knowledge.
- Environmental understanding and human behaviour is a core challenge for automated vehicles.
- Many situation predictions for pedestrians might be plausible.
- Motion planning with pedestrians is a safety critical application; environmental influences, intention changes, perception, interaction and personal aspects are not directly testable in a randomized controlled experiment.
- Personal aspects, interaction, perception, intention changes and environmental influences on pedestrians must be tested.

Section IV-A features ideas on the representation of a real environment in a virtual framework based on current technologies. A virtual environment is proposed as an indoor solution in section IV-B. The virtual environment can be extended in a large scale network (see section IV-C), where pedestrians can be integrated into an environment with virtual reality glasses, motion capture systems and driving simulators. As a result, real vehicle environments can be simulated with different environmental conditions.

### A. Environmental modelling

Four different representations of the town hall square in Vienna are shown (Fig. 6). With current technologies it is possible to track pedestrians' movements via cloud or network systems to get information how a pedestrian moves in a certain environment. For the virtual test environments described in the next sections it is also necessary to use 3D models to stimulate the perception of the test person, who should behave like a pedestrian. There is a need for a realistic and often computationally expensive rendering to represent realistic virtual 3D environments.

### B. Solution with virtual reality

A solution for testing safety critical systems with pedestrians is illustrated in Fig. 7. The movements and gestures of a test person acting like a pedestrian in a real environment are recorded (e.g. motion capture system) and the perception of the pedestrian is stimulated by virtual reality glasses (e.g. oncoming vehicle and buildings), Fig. 7-4. The software of motion planning can be integrated in the virtual environment, so that safety critical scenarios can be tested. The advantage of this approach is that interaction, real pedestrian behaviour, environmental influences and personal aspects can be incorporated into the test. The perception of the test person is stimulated by virtual reality glasses (e.g. oncoming vehicle and buildings). The whole experiment is visualized in a virtual environment (Fig. 7-1), processed by a processing unit (Fig. 7-2). Safety critical systems (e.g. motion planning algorithm with VIL) can be tested (Fig. 7-3). Other features of the highly active research area in immersive virtual reality can extend the test environment. An example are walking in place platforms [26].

### C. Perspectives in a large scale environment

A natural extension to the small-scale solution of section IV-B is illustrated (Fig. 8) to incorporate many test persons in different real world situations as a kind of virtual online game. In these large scale experiments persons from different cultures and social backgrounds can be incorporated in the virtual environment with virtual reality glasses, driving simulators and motion capture systems. Automotive companies can test their software incorporating existing SIL, PIL, HIL, VIL technologies. Engineers, psychologists and experts from different disciplines can analyse the behaviour of the pedestrians and the performance of developed algorithms and systems with(out) stimulating the environment. Global behaviour of pedestrians, external influences, personal aspects and interaction will be testable in this *Pedestrian and Environment in the Loop* approach. Google Street View [27] and Google Earth [19] are examples of large scale virtual environments, where interfaces for virtual reality glasses and motion capture systems can be incorporated.

### D. Limitations

Sickness of motion and the amount of computations is a disadvantage of this approach. In a future paper solutions with augmented reality devices and experimental settings will be proposed. The amount of time to model virtual environments, the amount of hardware and the processing is lower with use of augmented reality glasses.

## V. Conclusion

Currently, driving situations with pedestrians are often tested in observational statistical studies rather than in a randomized control experiment, due to safety reasons. This has an enormous impact on the development of motion planning strategies (conservative configuration) in autonomous vehicles and the usage for real scenarios (low generalizability, some aspects are not tested, i.e. intention, environmental aspects). The behaviour of pedestrians can be detected by onboard-sensors of the vehicle, wearables, smartphones, or cloud services and sensor networks (e.g. webcams). A randomized control experiment is proposed with the incorporation of virtual technologies. The advantage is that real test persons can be incorporated in an experiment (Pedestrian in the loop).

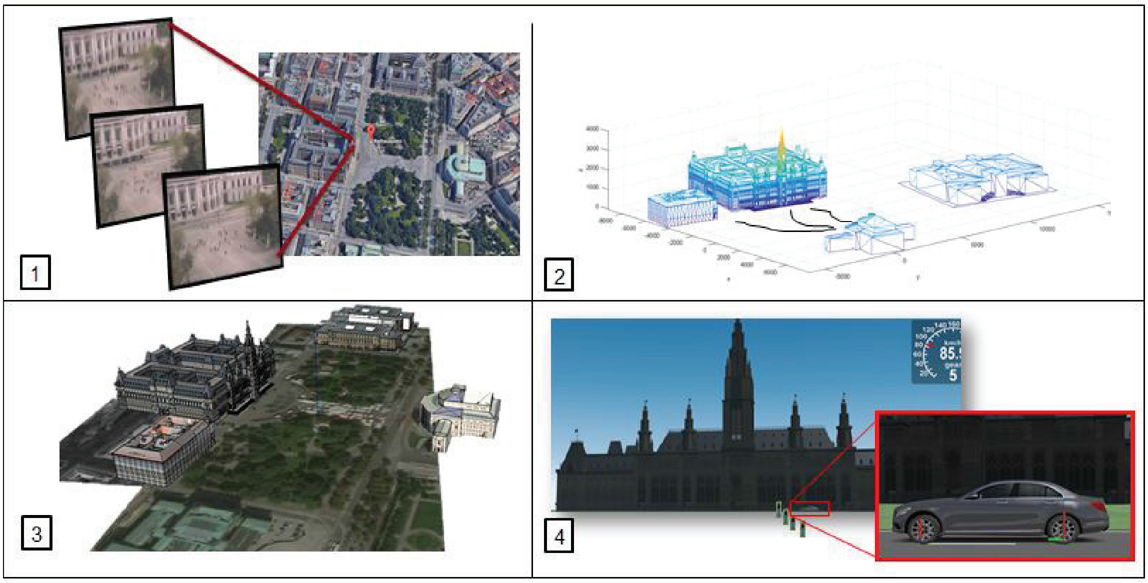


Fig. 6. Four different representations of town hall square in Vienna [18]: 1. Pedestrian detection with webcams and Google Earth [19], 2. Matlab [20] models of famous buildings around the town hall square, 3. Virtual representation with SketchUp [21], 4. Simulation in IPG CarMaker [22]

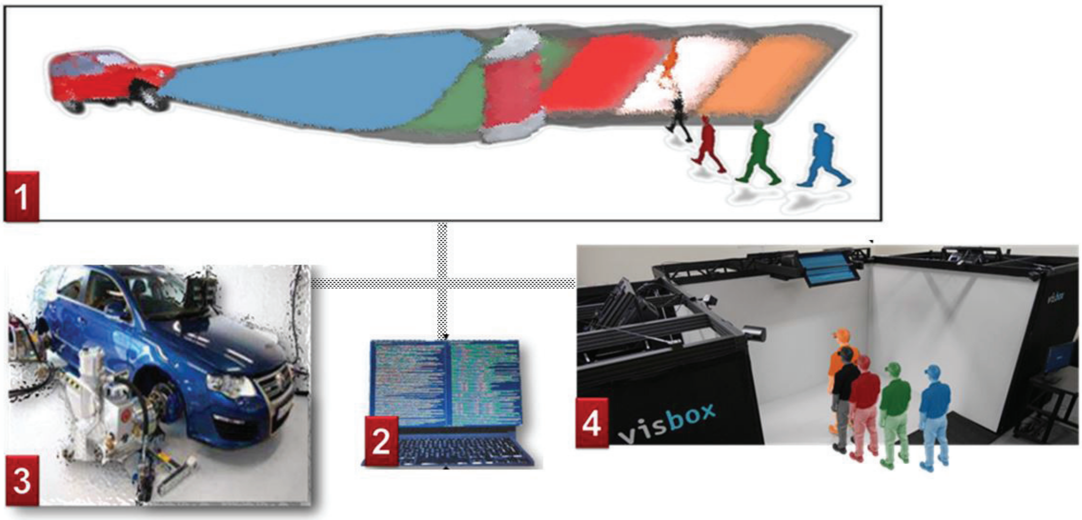


Fig. 7. Incorporation of real test persons for virtualization of collision avoidance scenarios with real traffic. 1: Virtual environment of collision avoidance scenario. 2: Processing unit. 3: Vehicle in the Loop (SIL, PIL, HIL also possible). 4: Incorporation of test person with virtual reality glasses, position estimation and motion capturing. Sources of illustrations: [23], [24], [25]

It is easily possible to change the virtual environments and to stimulate the perception of the test person. Deterministic mechanics of the human body (i.e. joint angles) can be measured with motion capture systems. Experiments with different persons offer new perspectives for the development of autonomous vehicles. Examples are tests for risky and safe motion planning and analysis of influences of interventions described in [14]. To extend the whole experiment it is also proposed to incorporate huge environmental structures, real world events and network systems (e.g. online games, world wide web). Engineers could incorporate safety critical systems for performance testing in real world scenarios which would help accelerate the transition to autonomous vehicles.

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[3]Interdisciplinary Training Network in Multi-Actuated Ground Vehicles. Links: https://iteam-project.net/; https://www.tugraz.at/en/tu-graz/services/news-stories/talking-about/singleview/article/die-schoenheit-der-ungewissheit-und-ihre-gefahr/


Fig. 8. Solutions for virtualization of collision avoidance scenarios and real traffic scenarios with incorporation of real test persons. Incorporation of huge amount of persons with a networked virtual system. 1: Person with virtual reality glasses. 2: Virtual Reality online game. 3: Real person with virtual reality glasses and motion capture system. 4: Experts, Specialists and Psychologists analysing the behaviour of people in the environment. 5: Vehicle in the Loop (or "SIL, PIL, HIL"). 6: Real drivers in a driving simulator

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