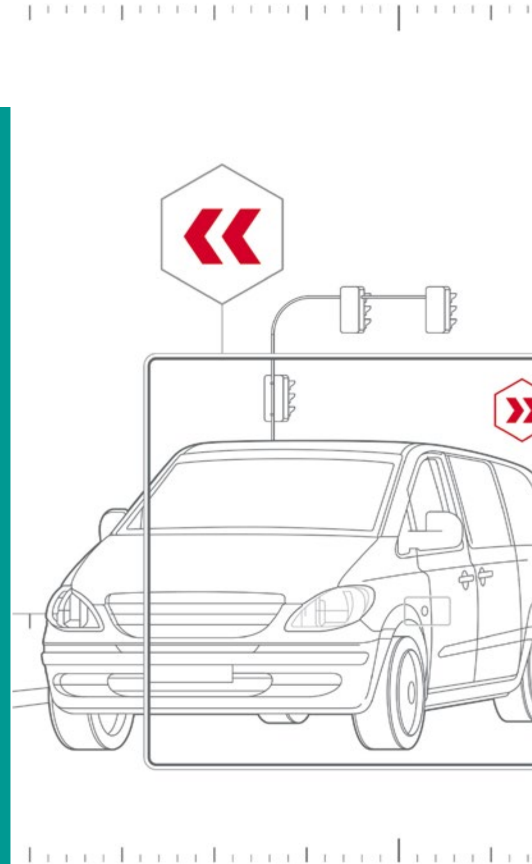

Validation of Autonomous Vehicles

Automated and connected driving up to autonomous vehicles is increasingly being used. But the distrust in their reliability is growing. The underlying algorithms are difficult to understand and thus intransparent. Traditional validations are complex, expensive and expensive. In addition, no transparent coverage for regression strategies for upgrades and updates is achieved. In this article Vector Consulting and the IAS of the University of Stuttgart show that classical methods have to be supplemented with cognitive test methods.

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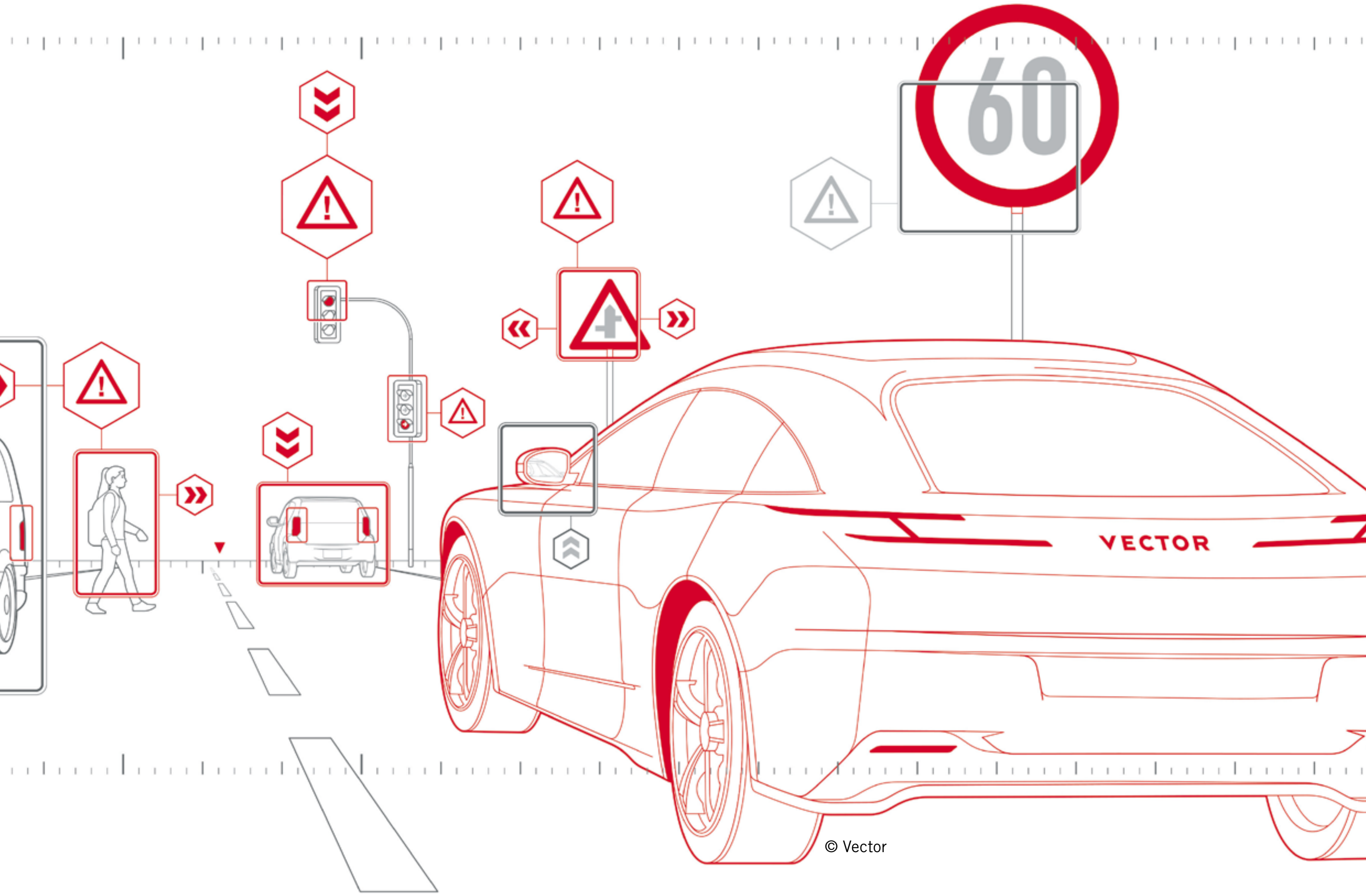
AUTONOMOUS VEHICLES

Society today depends on autonomous systems. Often, we do not even recognize them which is the ultimate proof of the Turing test. The potential of automated and autonomous driving systems is enormous: for example, the use of autonomous vehicles will eliminate up to 90 % of accidents and reduce up to 50 % of commuting time per user per day [1]. **FIGURE 1** indicates the five steps from automation to autonomy as also known from human learning. Those steps exemplify the way of a simple and "assisted behavior" in terms of low-level sensing and control towards "full cognitive systems" with a very high degree autonomy.

A completely autonomous car on level 5 is expected to drive with no human intervention even in dire situations. This implies that the cars must have intelligence at par or even better than humans to handle not just the regular traffic scenarios, but also the unexpected ones. Although several players such as Google and Uber are granted permission to operate their self-driving services, incidents such as the death of a driver put our faith in these cars to a test [2]. It is therefore quite apparent that existing validation measures aren't enough. New test methods are needed that can envision fatal traffic situations that humans haven't encountered yet. In addition, testing cannot simply be isolated to final stages, but must be part of every stage in product lifecycle. Hence, a sensible engineering process has to be adopted in developing autonomous cars that puts enough emphasis on testing and validation. Unlike an automated system which cannot reflect the consequences of its actions and cannot change a predefined sequence of activities, an autonomous system is meant to understand and decide about how to execute based on its goals, skills and a learning experience.

This article introduces validation and certification as well as the general approval (homologation) of autonomous vehicles and their components. It pro-



vides insights into the validation of autonomous systems, such as those used in automation technology and robotics and gives an overview of methods for verification and validation of autonomous vehicles, sketches current tools and shows the evolution towards AI-based techniques for the influence analysis of continuous changes.

VALIDATION OF AUTONOMOUS VEHICLE SYSTEMS

Autonomous vehicle systems have complex interactions with the real world. This raises many questions about the validation of autonomous vehicle systems: "How to trace back decision making and judge afterwards about it?", "How to supervise?", or "How to define reliability in the event of failure?". **FIGURE 2** provides an overview on validation technologies for autonomous systems. The transparency of the validation is horizontally distinguished. Black box means that there is no insight to the method and coverage, while white box provides transparency. The vertical axis classifies to the degree we can automate the validation techniques and thus for instance facilitate regression strategies with software updates and upgrades.

TABLE 1 provides a complete evaluation on static and dynamic validation technologies for autonomous systems. It mentions some tools, but they are to be seen as an impulse, rather than a complete list or even a recommendation. Every company today implements its own methodology and development environment. Too often one sees ambitious development teams, complex tool

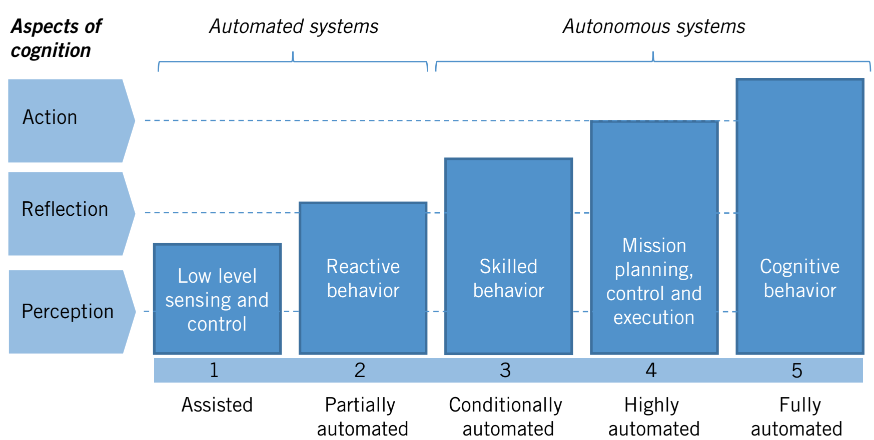


FIGURE 1 From assisted to fully automated (autonomous) systems (© Ebert|Weyrich)

Method	Charac-teristics	Tool Support, Technologies	Cover-age	Regression strategy	Strength	Weakness	Effective-ness	Effici-ency
Modeling and simulation environments with SIL, HIL, MIL	Static and dynamic	Model checker, e.g. Matlab, dSPACE, Vector VT System, NovaCarts, Vires, PreScan	0	Repeat impacted scenarios (low efficiency)	> Reduces validation cost. > Decouples hardware and software development.	> Brute Force, for high coverage. > Too much oriented towards components > Tests only for known scenarios. > Scenario banks are not comprehensive to validate autonomous systems > Intransparent dependencies	0	0
Function test	Dynamic, all functions	Modeling tool for functional abstraction with unit test tools (Ex: JUnit, PHPUnit), dedicated test environments for stub generation	0	Repeat functional test cases for impacted functions	> Tests all AI aspects: sensing, decision making and action taken. > Validates all the functional requirements.	> Too much oriented towards components. > Insufficient to validate complete systems	0	+
Integration test	Dynamic	Test suites, test management, Combinatorial tools such as AETG, Citrus etc.	0	Regenerate test cases	> Tests integration of components.	> Large number of interfaces: easy to miss some links. > Fault localization is difficult.	+	+
Fault injection	Static for residual defect estimation	Test environment and defect modeling e.g. beSTORM, Security Innovation	–	Introduce few selected defects	> Provides estimate on residual defects and coverage. > Exposes weak, enabling designers to strengthen them.	> Need concrete understanding of underlying system architecture and behaviour.	–	–
Negative requirements with misuse, abuse, confuse cases	Static specifically for Safety, Security, Usability	Directly modeled and traced with requirements tools, e.g. DOORS, Visure, PTC, PREEvision, Enterprise Architect, HP ALM	0	Reuse situational negative cases	> Good for scenarios to be avoided. > Formalizes non-functional requirements. > Strengthens system security.	> Difficult to set up systematically. > No coverage schemes. > The test cases do not necessarily cover all possible negative cases.	+	+
FMEA, FTA	Static, specifically for safety critical systems	FMEA worksheets, component abstractions, reuse library	0	Retest for the changed components	> Well established for safety and security (attack tree). > Enables designers to foresee system interface failures.	> Depends heavily on human knowledge. > Labour intensive.	+	+
Experiments, empirical test strategies	Empirical test generation for load test, performance, thermal, etc.	Experiment specific test tools, such as Parasoft DTP, EggPlant, Thermal imager etc.	+	Repeat the test strategies for changed functions	> Relatively easier to frame the test cases. > Covers wide range of electrical systems.	> Depends heavily on human knowledge. > Labour intensive. > Very little or no test automation.	+	0
Specific quality requirements test e.g., pen testing, fuzzing	Dynamic, specifically for quality requirements	Dedicated test tools, e.g. automatic fuzzing extensions e.g. CANoe, OWASP ZAP, Vega etc.	–	Retest for impacted components	> Well established for security. > Effective in ensuring that the system meets known quality requirements.	> Often insufficient to validation complete system security and safety.	0	+
Brute force usage in real-world while running realistic scenarios	Dynamic for ensuring situational coverage	Recording and replay with actual scenario libraries with data loggers from various sensor systems, e.g. Tecnomatix, CarMaker, EB Assist, CANape	0	Repetition (low efficiency)	> Closest to real-world and thus highly effective > Validates all systems at once > Comprehensive view and coverage > Standardizes scenario storage format and tagging	> High effort to capture all relevant scenarios with underlying real-time data analysis > Unclear coverage > Most of the test cases are redundant > Intransparent situational coverage	+	–
Intelligent validation e.g., cognitive testing	Dynamic test generation and selection depending on situation and environment	Machine-learningframeworks, such asTensorflow, Apache Spark, and so onOpen data sets, such as nuScenes`	+	Reuse generated test cases from dependency database	> Improved transparency > Automatically considers dependencies to external environment and internal functions > Automates major part of test procedure > Standardizes scenario storage format and tagging > Sharing test scenarios across V-Model abstraction levels	> High effort to set up AI based test environment. > Needs large computation power > Growing discipline, i.e. not much method and tools available	+	+

TABLE 1 Evaluation of validation technologies for autonomous systems (© Ebert|Weyrich)

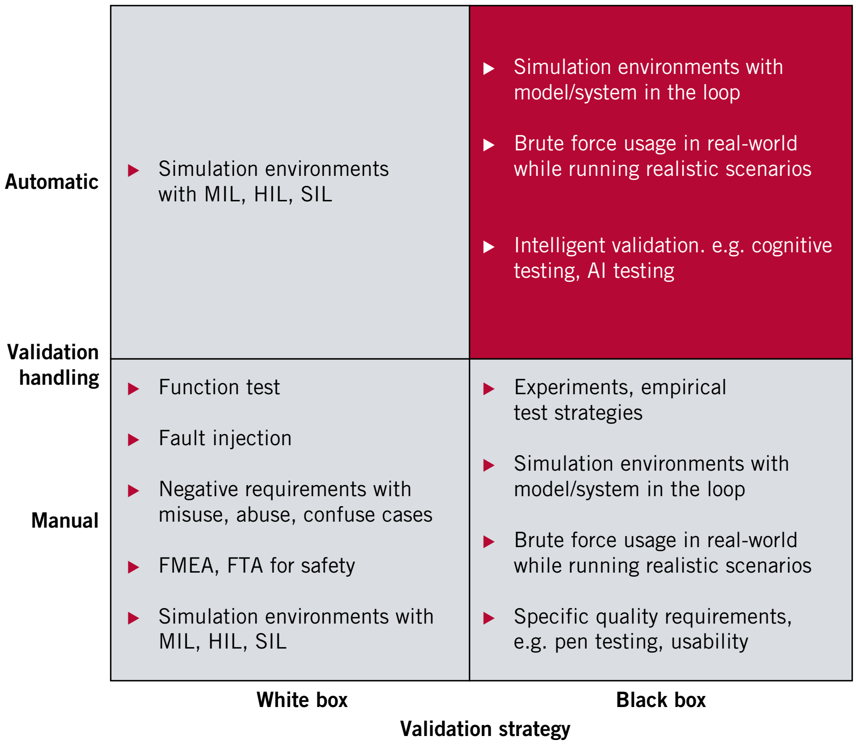


FIGURE 2 Validation technologies for autonomous systems (© Ebert|Weyrich)

chains, but no tangible sustainable testing strategy.

Positive testing methods aim to ensure that all the functional requirements of the system are taken care. While the negative testing methods ensure that the system is tested for all the non-functional requirements. Negative requirements (f.e. safety and cyber-security) are typically implied-requirements and are not explicitly specified in System Requirement Specifications (SRS). The following sub-sections explain how these methods are applied to validate autonomous cars.

Fault injection techniques make use of external hardware to inject faults into target system's hardware. Faults are injected either with or without direct contact with physical hardware. By having direct contacts, faults such as forced current addition, forced voltage variations etc. can be injected to observe the behavior of the system. Faults can also be injected without make physical contact using methods such as heavy-ion radiation, exposure to electromagnetic fields etc. Such fault injections can cause bit flips, failure of hardware etc. which are not tolerated in safety critical systems.

Functionality based test methods categorize the intelligence of a system into three categories: 1. Sensing functionality, 2. Decision functionality and 3. Action functionality. The idea behind such methods is that the autonomous vehicle should be able to retrieve various functionalities for a given task analogous to human beings. For example, the vehicle should be able to recognize vehicles, pedestrians etc. for vision-based functionality. Combinations of these recognized objects can then act as inputs to decision functionality and several decisions can then lead to actions. Functionality-based testing therefore breaks down the scenarios into various functional components which can be tested individually.

Simulators are closed indoor cubicles, which act as substitute to physical systems. These simulators can simulate the behavior of any system either by using physical hardware or by using the software model. The behavior of driver can then be captured by feeding him simulated external environment. Since the simulators employ hydraulic actuators and electric motors, the inertial effects generated feel nearly the same as real system. They are used for robots in industrial automation and surgery planning in medical, train systems and automotive.

Nothing can come close to the real world than the real world itself. This is perhaps the final validation phase where completely ready system is driven out into real roads with real traffic. The sensors data is recorded and logged to capture the behavior in critical situations. It is then later analyzed to accommodate and fine tune the systems according to real word scenarios. The challenge in this stage however lies in the sheer amount of test data that is generated. A stereo video camera alone is found to generate 100 GB of data for every kilometer driven. In such situations, big data analysis becomes extremely important. The approval of autonomous vehicles therefore requires regressive validation, i.e., a test that, after changing the control algorithms, performs a new check and ensures the function. Thus, safety, reliability and reliability can be obtained both in development, testing and in use, even when the system adapts, i.e. is changed.

While still relevant, traditional validation methods are not enough to fully test the growing complexity of autonomous cars. Machine learning with situational adjustments as well as software updates and upgrades require novel regression strategies. Intelligent validation techniques tend to automate complete testing or certain aspects of testing, **FIGURE 3**. This eliminates the potential errors associated with manual derivations of test cases since humans may fail to derive or think about certain scenarios. It also eliminates the enormous amount of time that needs to be invested to derive the test cases. The following sub-sections summarize some of the papers that attempt to derive such validation techniques.

Truly transparent validation methods and processes become of an uttermost relevance and will be challenged by the progress of technology over the five sketched steps towards autonomous behavior. Although still relevant, traditional validation methods aren't enough to completely test the growing complexity of autonomous cars. Machine learning with situational adaptations and software updates and upgrades demand novel regression strategies.

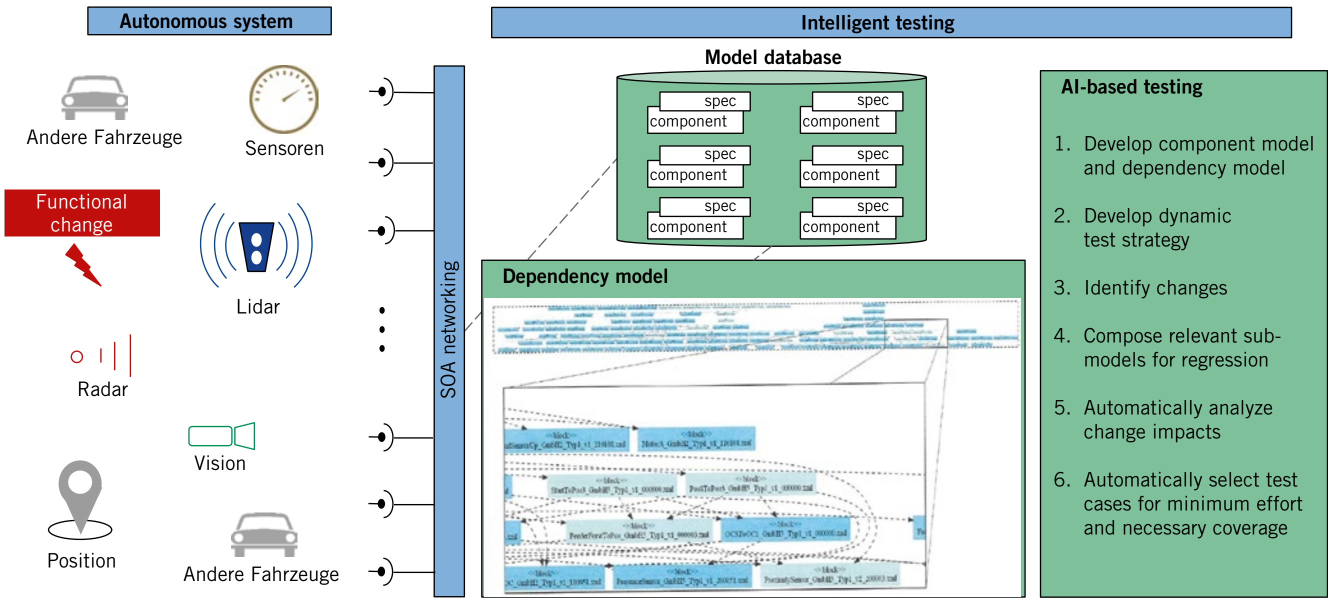


FIGURE 3 Cognitive testing for autonomous vehicles (© Ebert|Weyrich)

COGNITIVE TESTING

With artificial intelligence and machine learning, we need to satisfy algorithmic transparency. For instance, what are the rule in an obviously not anymore algorithmically tangible neural network to determine who gets a credit or how an autonomous vehicle might react with several hazards at the same time? Classic traceability and regression testing will certainly not work. Rather, future verification and validation methods and tools will include more intelligence based on big data exploits, business intelligence, and their own learning, to learn and improve about software quality in a dynamic way. Cognitive test procedures are based on a database that transparently depicts scenarios and disruptions, so that a target behavior for critical situations, boundary conditions, etc. is defined. In the signal path, signals are generated from the scenarios for the interfaces of the autonomous system or its components. For example, if a child playing suddenly appears in front of the vehicle, the reaction becomes the overall system or the action of its components, e.g. his steering, tested. These signals can be simulations for camera and radar sensors, but also communication signals, such as Car-to-X, residual bus simulation and the display of disturbances.

By parameterization special cases, such as different lighting conditions, can be displayed. From the behavior of the system under test actual rules are extracted, which are compared with the expected target behavior. The automatically extracted actual rules are compared with known and accepted target rules as to how the system under test should behave in the scenario. The target rules are derived from laws, experiences, human expertise, guidelines from ethics committees but also from simulations. They should be transparent and therefore accessible to human testing. Rules are extracted from the behavior of the autonomous system under test in order to make transparent the learned intransparent behavior stored in implicit rules or neuron links. These now transparent but quite fuzzy rules are compared with the set rules in behavior. The validation and certification is based on the control deviations [5,7,8,9].

FIGURE 4 gives an overview of the cognitive testing we are currently using for networked components of autonomous vehicle systems. Unlike Brute Force, the dependencies between the white box and the black box are considered, bringing efficiency and effectiveness into line. Automotive functions consist of the interaction of many components, such as controllers, sensors and actuators, which are distributed in the system. In a distributed overall system, undesirable behavior and basic malfunctions can arise because there has been a software change at one point that breaks through to other components. This raises numerous questions: How can the function of a system be ensured if changes take place in the subcomponents? How can the safety and reliable behavior be guaranteed if software changes are made to individual components during operation?

A key question is in which way an artificially intelligence can support the process of validation. Obviously, there is many AI approaches ranging from rule-based systems, fuzzy logic, Bayesian nets to the multiple neural network approaches of deep learning. However, the process of validation of an autonomous system is multilayered and rich in detail. Various levels of validation tests can be distinguished, such as the systems level, the components or modules.

The potential for an intelligent testing is manifold: On a system level there are questions on which test cases must be executed, and to what extent? This means an intelligent validation is requested to help in terms of selection or even creation of test cases for validation. In a first step an assistance functionality which helps to identify priorities in an existing set of cases. As a result, the validation expert can test quicker and with a better coverage of situational relevant scenarios. On the level of a component or module testing it is also required to identify relevant cases. This can range from a simple support on how to feed the system with adequate inputs and check on the outputs to complex algorithms which

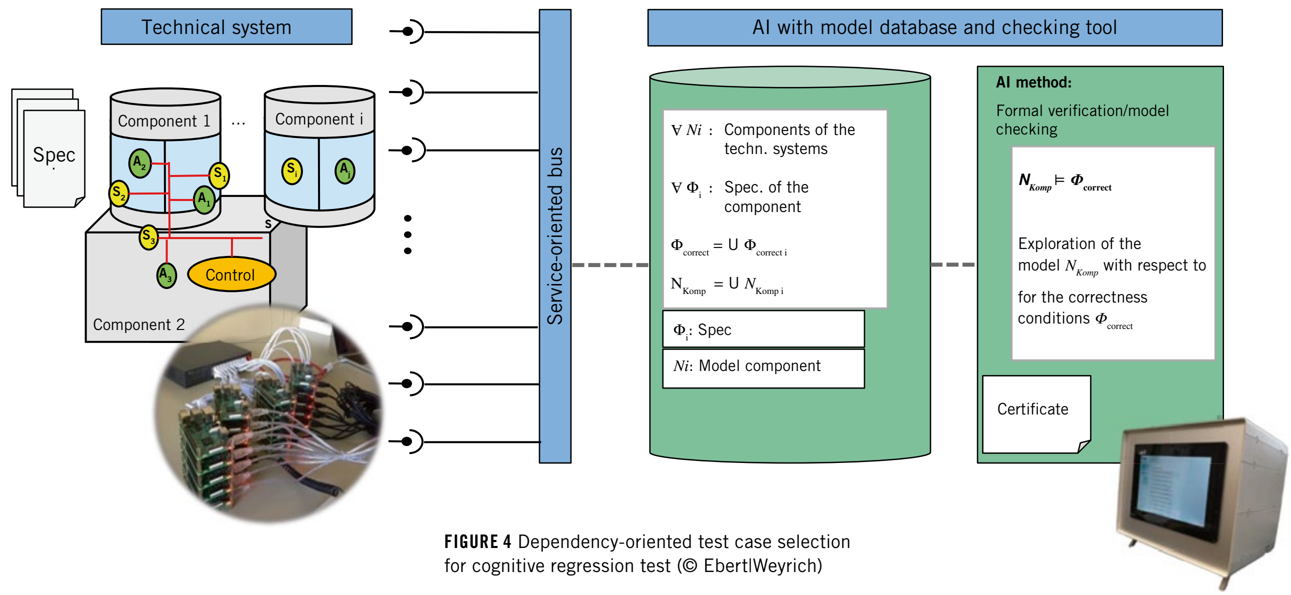


FIGURE 4 Dependency-oriented test case selection for cognitive regression test (© Ebert|Weyrich)

automatically create test cases based on the code or user interface.

PERSPECTIVES

With the growing importance, and hence the concerns of users and policymakers regarding the impact of autonomous systems on our lives and society, software engineers must ensure that autonomous functions and systems function reasonably well and properly. To build trust, the quality of the technical system is expected to be at least an order of magnitude higher than that of human-powered systems. Building trust is closely linked to issues of validation. However, such validations depend on many factors. Autonomous vehicle systems provide efficiency and safety by relieving the operator of tedious and error-prone manual tasks. The question "Can we trust autonomous vehicles?" Will continue to grow in the coming years. Public trust in autonomous vehicle systems depends heavily on algorithmic transparency and continuous validation.

An accident caused by software errors is discussed more intensively today than the many accidents caused by alcohol. On the other hand, current software errors with deaths in aviation also show a certain "habituation". The number of passengers does not decrease because of crashes, as everyone knows that the aircraft are altogether safely developed. This learning curve of acceptance can be seen in all autonomous systems, historically for example in smartphones, bots with automatic speech processing and in social networks. An increasingly informed society accepts that while software is never error-free, so there is a residual risk, there are still many advantages over the past.

With a growing concern of users but also policy-makers on the impact of autonomous systems on our lives and society, software engineers must ensure that autonomy acts better than humans. Clearly, we do not talk here about few percentage points. To build trust we rather need at least one order of magnitude better quality compared to human operated systems. It is above all a question of validation to achieve trust. Alan Turing who was one of the first to consider AI in real life remarked wisely: "We can only see a short distance ahead, but we can see plenty there that needs to be done". This remains true for a rather long transition period, and intelligent validation will play a pivotal role.

REFERENCES

[1] Gao, P., H.-W. Kaas, D. Mohr, and D. Wee: Automotive revolution: Perspective towards 2030. McKinsey, 2016.
[2] Heerwagen, M.: Rechtlich Ausgebremst. ATZ Elektronik, Dez. 2018, S.8-13
[3] Ebert, C.: Requirements Engineering. dPunkt, 6th edition, 2019.
[4] ISO: Road vehicles—Safety of the indented functionality, International Organization for Standardization. ISO 21448, 2019.
[5] Santori M. and D. A. Hall. (2016). Tackling the test challenge of next generation ADAS vehicle architecture. National Instruments. http://download.ni.com/evaluation/automotive/Next_Generation_ADAS_Vehicle_Architectures.pdf
[6] Rodriguez, M., M. Piattini, and C. Ebert, "Software verification and validation technologies and tools,". IEEE Softw., vol. 36, no. 2, pp. 13–24, Mar. 2019.
[7] Ebert, C.: "Rule-based fuzzy classification for software quality control," Fuzzy Sets Syst., vol. 63, no. 3, pp. 349–358, May 1994. doi: 10.1016/0165-0114(94)90221-6.
[8] Zeller, A. and M. Weyrich, "Composition of modular models for verification of distributed automation systems," in Proc. 28th Int. Conf. Flexible Automation and Intelligent Manufacturing (FAIM2018), Columbus, USA, 2018, pp. 870–877.
[9] Shalev-Shwartz, S. et. At.: On a Formal Model of Safety and Scalable Self-Driving Cars. Intel, www.mobileye.com/responsibility-sensitive-safety, continuously enhanced.