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Simulation Platform from Data Collection to Impact Assessment of Autonomous Vehicles

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Abstract

Automated vehicles are expected to bring major changes in the driving task, the mobility patterns and have significant impacts on critical areas such as traffic safety and efficiency, environment or public transportation systems. The analysis of the behavior of autonomous vehicles is a holistic approach starting from the data collection either from the vehicle itself or the infrastructure, surveys and social media to understanding, modelling and simulating automated vehicles. The aim of this work is to graphically depict the structure of a platform illustrating this holistic approach, its various components and their interrelations.

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Keywords: automated vehicles; simulation platform; impact assessment; modelling; data collection

1. Introduction

Automated vehicles (AV) have a wide variety of functions and systems that can assist the driver with the primary driving tasks, while autonomous vehicles can fully undertake vehicle control without the need for driver supervision. The design, construction and operation of the equipped vehicles should ensure safety for the driver, the passengers and for the interaction with conventional vehicles and vulnerable road users. The increased penetration rate of these new vehicles highly depends on public acceptance (Orfanou et al., 2022, Xu et al., 2018) and their impacts on critical areas such as safety, traffic conditions, environment or public transportation reliability (Oikonomou et al., 2020).

Past and present research focuses on specific aspects of automated vehicles such as modelling and simulating their behavior, assessing their impacts or investigating users' perception through surveys. In reality, there is a strong connection between the different steps of analyzing AVs, e.g. data from questionnaires can reveal what could be

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improved in the reactions of the equipped vehicle or which characteristics of their behavior were accepted or not. These data combined with the data collected from the test vehicles can result in developing an accepted driving autonomous vehicle behavioral model that could be imported in a simulation tool and assess the impact of this profile on critical areas. Therefore, a more holistic approach is necessary to be formulated covering all aspects of autonomous vehicles and a pipeline should be developed including all processes from data collection through real world experiments and questionnaires to modelling and impact assessment, describing each step and the connections and interrelations among each other.

The aim of this work is to graphically depict the structure of a platform consisting of all the above mentioned components illustrating the process from data collection to modelling and impact assessment of automation as well as their interrelations. The proposed developed platform aims to analyze big data collected from AVs through their various sensors combine with the results from surveys and social media posts and therefore to formulate an accepted “driver” behavioural model. This model is then integrated in a simulation software for assessing the impact of automation on various areas by formulating different scenarios and use cases. Despite the fact that nowadays vehicles with several automated function are already in the market while fully autonomous vehicles are still under development and testing, the proposed simulation platform can be applied to all levels of automation.

2. Related work

Various platforms have been developed dealing with different aspects of autonomous driving and its functions such as the CARLA (https://carla.org/), an open source simulator for training and validating autonomous driving systems allowing the integration of different sensor data and the generation/execution of multiple scenarios. C-Roads platform (https://www.c-roads.eu/platform.html) is focusing on the deployment of C-IT systems and the cooperation between stakeholders operating in the field of automation (e.g. authorities, road operators) while the NVIDIA DRIVE Sim platform tests autonomous systems by generating ground-truth synthetic data and running various scenarios reducing the requirements of real test beds and driving conditions (https://www.nvidia.com/). Best et al. (2018) developed AutonoVi-Sim, a simulation platform which enables data export from vehicle’s sensors and testing of different algorithms under different weather ad traffic conditions while through the 4 – layers platform developed by Chen et al. (2018) based on hardware in the Loop system, it is feasible to simulate vehicle sensors, construct car kinematic models, test path planning and decision making algorithms as well as simulate interaction between autonomous vehicles and other road users. Other simulation platforms developed for testing and validating autonomous driving are the Autonomous Robotics Simulation Platform developed by Congata (https://www.cognata.com/), Deepdrive (https://deepdrive.io/index.html), AirSim (https://microsoft.github.io/AirSim/) , the platform developed by Foretellix (https://www.foretellix.com/), the AI- platform by Morai (https://www.morai.ai/) and the simulation platform in 3D virtual environment for testing the reaction of AVs developed by Aparow et al (2019).

3. Components and Tools

The developed platform consists of five interrelated components (Fig. 1): i. the automated vehicle monitoring component, ii. the external information component, iii. the data preparation module component, iv. the behavioural modelling and v. the impact assessment. In each component, different functions and actions are executed and different data and tools are required. The data collected from the various sensors of the automated vehicle describe its behavior under various conditions, their interaction with other vehicles and road users along with the vehicle’s reaction in emergency situations. These data are used for training and then validating a data driven model in order to formulate the set of parameters governing the AV behaviour. The output of the data driven models can be used either to parameterize existing behavioural models (car following, agent- based, cellular automata, etc.), or to develop a new one. Additionally, in order to test and investigate the formulated model and its influence on different impact areas, a scenario generating tool should be developed generating automatically various scenarios that can be seamlessly imported in the simulation. Finally, the simulation tool which is the last part of the process is an open source microscopic simulation software (e.g. SUMO) that will be used for the simulation test runs.

Using different scenarios, the impact assessment of the AVs will be evaluated under different conditions and circumstances. Interestingly, in this process a component that handles external information is very critical. The external information could be either static data from surveys on importance, attractiveness and acceptance of new systems, or structured and unstructured data such as weather conditions, incidents and sentiments coming from social media or other sources. This usually aggregated information can be critical in identifying the aspects of the system or the conditions that may increase acceptance of automation.

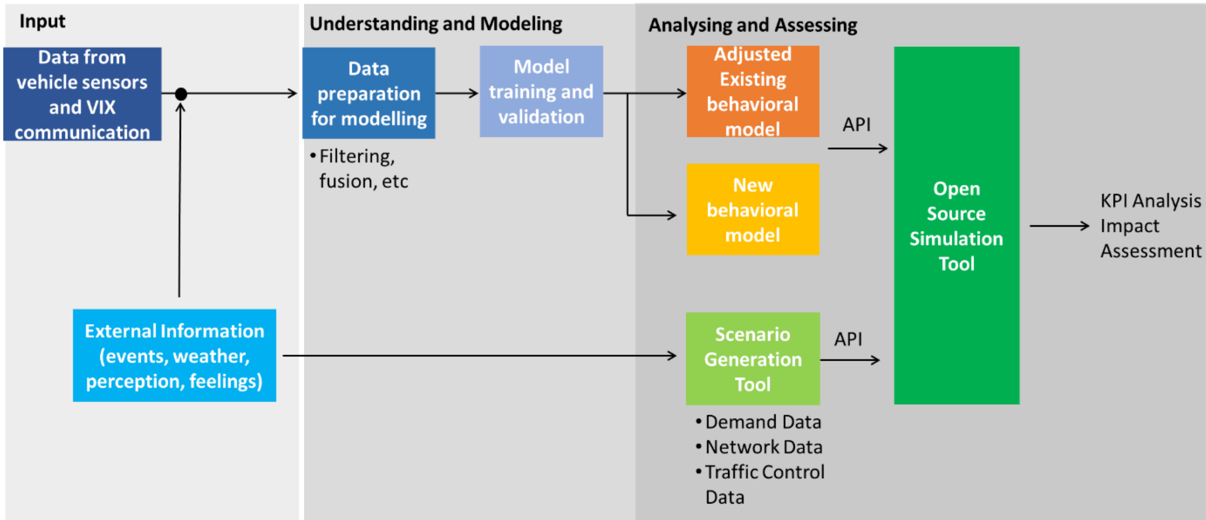

Fig. 1. The complete suite for testing acceptance

4. UML Class Diagram

A class diagram in the Unified Modelling Language (UML) is developed based on the concepts of Figure 1, which graphically represents the static structure of object-oriented systems, which are comprised of the following elements: classes, attributes of classes, methods (operations of classes and relationship among objects. A class constitutes a blueprint for an object. Object-Oriented Design is based on class definition, since objects are created from classes. Classes describe the general type and properties of objects, while objects are usable instances of classes. Each object is built from the same set of blueprints and therefore contains the same components (properties and methods). The standard meaning is that an object is an instance of a class and has states and behaviours.

Classes encompass attributes (state) and methods (behaviour). Each attribute has a type (e.g. int, float, string, array, vector etc.) and each operation has a signature (i.e. type of data that returns after operating). Classes are represented by rectangular shapes which are partitioned in three sections. The first section includes the class name, the second section shows attributes and their types, while the third one depicts methods and their return types. Attributes map onto member variables (data members) in code, while methods map onto class operations in code.

The -, #, and + symbols before attribute and method names in a class indicate the visibility of the attribute and the operation.

- \- indicates private attributes or methods,
- \# indicates protected attributes or methods,
- \+ indicates public attributes or methods.

Each parameter in a method may be denoted as “in”, “out” or “inout” which specifies its direction with respect to the caller. This directionality is shown before the parameter name. The degree of detail incorporated in UML class diagrams is highly correlated with the maturity of the development process. In the early stages of system formulation, the diagram depicts information at conceptual level. Subsequently, focus is placed on the interfaces of

Abstract Data Type (ADTs) in the software (specification phase). Finally, a description is provided with respect to the implementation of class interfaces (implementation phase). Granularity affects the amount of detail to be given and the types of relationships worth presenting.

UML precisely conveys how code should be implemented from class diagrams. The latter entails interpretation of UML class relationships. A class may be involved in one or more relationships with other classes. A relationship can be one of the following types:

- Inheritance: Relationship between a more general classifier and a more specific classifier. Represents an "is-a" relationship.
- Association: A structural link between two peer classes.
- Aggregation: A special type of association. It represents a "part of" relationship. Objects of classes associated with aggregation have separate lifetimes.
- Composition: A special type of aggregation where parts are destroyed when the whole is destroyed
- Dependency: A special type of association. Exists between two classes if changes to the definition of one may cause changes to the other (but not the other way around).
- Realization: Realization is a relationship between the blueprint class and the object containing its respective implementation level details. This object is said to realize the blueprint class. In other words, you can understand this as the relationship between the interface and the implementing class.

5. Integrated Simulation Platform as a UML Class Diagram

A UML Class Diagram (Fig. 2) with the characteristics and elements described in the previous section has been developed in order to depict the methodological framework and the simulation platform for modelling and assessing autonomous vehicles impacts as shown in Fig. 1. More specifically, the integrated simulation platform consists of 5 different elements: data, modelling, use cases, simulation platform and impact assessment and each one of them includes a variety of classes further explained in the following paragraphs.

The data collection part includes all the possible sources and ways data is collected concerning autonomous vehicles, their behaviour and reaction as well as public acceptance and people's perception towards automation services and functions with or without having an experience with such an intelligent vehicle. The data sources can be interviews and questionnaires aiming to reveal what people think about automated vehicles, their attitude and willingness to use one before or after experiencing driving or riding an automated/autonomous vehicle. Trust towards the machine, the skills users believe are required for driving in automated mode or handle a transition of control (from manually to automated), feelings and emotions while using an automated vehicle, or the user friendliness of the HMIs and the various systems can also be evaluated. Several types of questionnaires serving all the above purposes have been created such as the User Profile Questionnaire (UPQ), the User Experience Questionnaire (UEQ) (Schrepp et alo., 2017), the Technology Acceptance Questionnaire (VDL) (Van der Laan et al., 1997), the System Usability Scale (SUS) (Brooke, 1996), the Trust Scale (Dehn, 2008), the Impact and Socio-Economic Questionnaire (ISE), the HMI Evaluation Questionnaire (HMIQ) and the Training Evaluation Questionnaire (TEQ). The second source of data comes from the vehicle itself through its various sensors (radar, lidar, ultrasonic, gyroscopes, GPS, accelerometer, ect), the infrastructure via cameras, radars, detectors and the vulnerable road users by recording and observing their behaviour when interacting with an automated vehicle. Finally, data isolated and captured from social media platforms and posts such as Reddit, Twitter, Facebook or YouTube using a lexicon of terms relevant to automated and autonomous driving and vehicles (Beigi et al., 2016, Gaspar et al., 2016) can also be used for capturing users' perceptions. Emojis and text are analysed through a sentiment analysis and negative/neutral/positive opinions about automated vehicles can be extracted.

Various use cases are formulated for all transportation sectors, pilots and road users (drivers/riders, passengers, vulnerable road users) for identifying factors increasing public acceptance under different (non) emergency situations, interaction with other road users and for different types of developed HMIs. The results of the data and use cases elements are feeding the modelling and simulation platform parts as shown in Fig. 2. In the modelling part, data collected are further analysed for extracting driving patters, profiles, driving parameters and accepted behaviours feeding the driver model that will be used for mimicking the AV behaviour. Car following, lane changing, data driven and other types of models are chosen for this purpose that can be found in Orfanou et al. (2022).

The driver model resulting from all the previous steps of data collection and analysis will be integrated in the main part of the UML Class Diagram which is the simulation platform. The model should be calibrated usually using ground truth point data or floating car data (Ciuffo et al., 2008). Calibration is the process that adjusts model parameters so that the simulated measurements (e.g. traffic volumes and speeds, path travel times) can match the field observed ones. The specific process is of outmost importance especially in cases where one wants to observe impacts in an implementation of a policy and, thus, requires a very accurate description of the traffic setup. Calibration is a time-consuming task, since micro simulation models entail a great level of traffic detail. For this, the calibration problem has been formulated as an optimization problem in which a large solution space exists due to a wide range of each relevant model parameters (Ciuffo et al., 2008). Since the calibration problem is not a classic optimization problem (no gradient information exists) to directly apply mathematical programming methods, researchers usually resort to metaheuristic methods, such as the genetic algorithm (GA)), simultaneous perturbation stochastic approximation (SPSA), the Tabu Search (TS) etc (Yu and Fan, 2017).

Apart from the model, the simulation platform includes the scenario generation tool and the simulation software and analysis. The scenario generation tool is basically a combination of vehicle types, penetration rates of automated vehicles in the simulated network, the driving styles (aggressive, normal, conservative, etc) and the respective driving model parameters. The simulation software and analysis can be distinguished into 4 different categories: macroscopic, mesoscopic, microscopic and agent-based. The last part of the UML Class Diagram is the assessment where the impact of automated vehicles on various critical areas, i.e. safety, personal mobility, vehicle operations, public transportation, traffic efficiency and environment, is estimated based on the selected Key Performance Indicators (KPIs) (Orfanou et al., 2022). The magnitude of the impact is estimated through the values the KPIs take, once the simulation is executed.

The diagram in Fig. 2 shows the various classes of each individual element, their defined parameters and the type of each parameter, e.g under the element “impact assessment” the following classes are distinguished: safety, environment, personal mobility, vehicle operations, public transport and traffic. Under the class environment, the float parameter fuel consumption is defined as a Key Performance Indicator (KPI). Apart from this information, the arrows shows the connection/communication between the elements and the input and output information between the classes.

6. Conclusion and Future Work

The proposed platform gives a detailed overview of all the interrelated aspects influencing the analysis and investigation of automated and autonomous vehicles and the individual facets that should be taken into consideration. It depicts the whole stepwise process that should be followed from data collection through the various sources to the impact assessment of automation on critical areas. A UML Class Diagram was developed for illustrating the different internal and external elements of a simulation platform as well as their interactions and interconnections. The diagram showed the process followed from data collection to impact assessment and various classes and their contents were defined and specified respectively. This process can be followed for all purposes, transportation sectors, modes and simulation goals. By quantifying and determining each individual element of the Class Diagram based on research study requirements many different applications can be achieved.

Future work includes the realization of the proposed diagram into a real suite, which will be an important tool for researchers and practitioners.

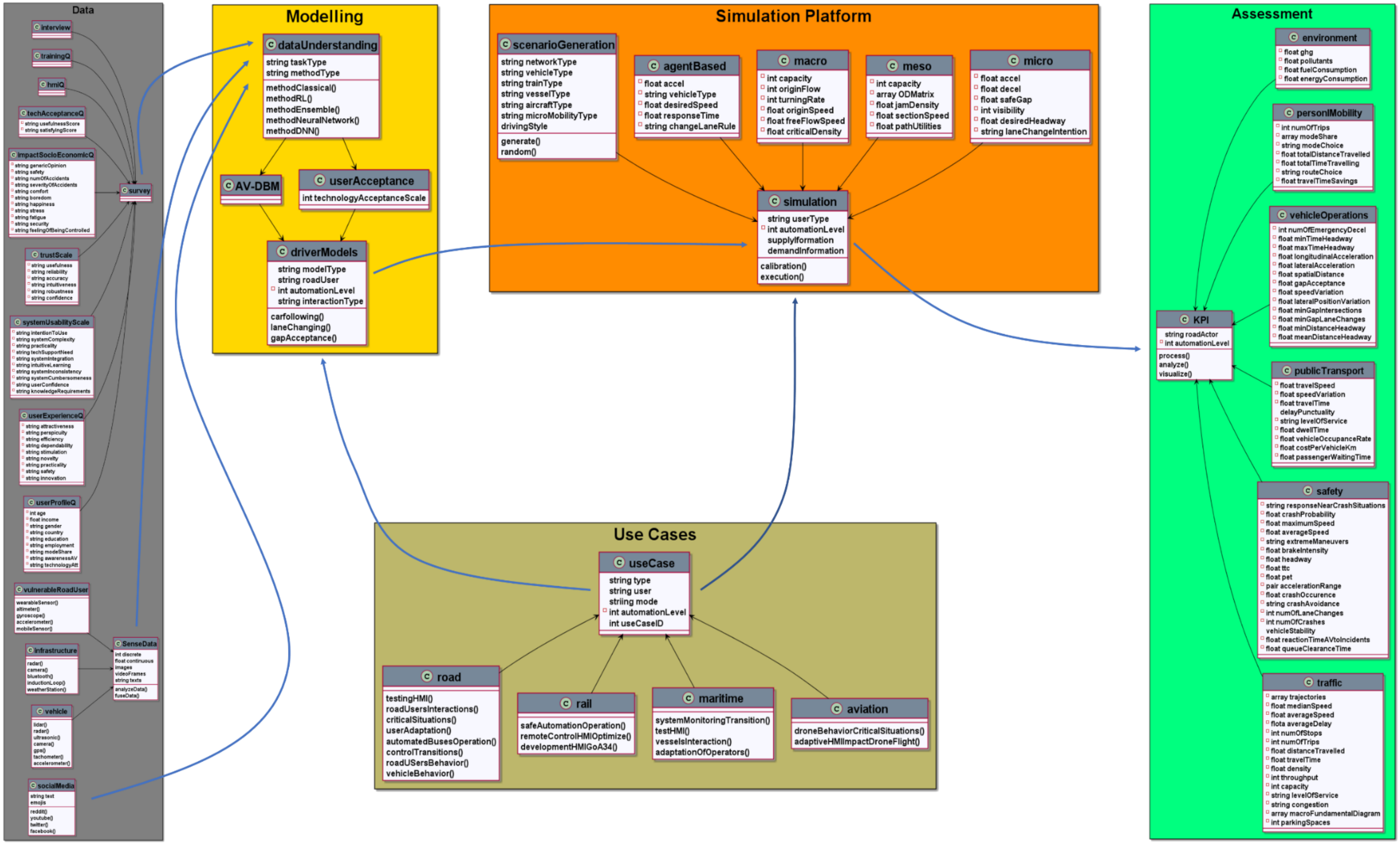

Fig. 2. The complete suite for testing acceptance as a UML Class diagram

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