A Dynamic and Model-Based Approach for Performing Successful Multi-Driver Studies

Julian Schindler [1], Frank Köster [1]

(1) German Aerospace Center, Braunschweig, Germany, e-mail: {julian.schindler, frank.koester}@dlr.de

Abstract *– When designing driving simulator studies, sometimes high efforts have to be spent to make them successful. Some drivers may not behave as desired, leading to situations unforeseen by the developers. When looking at multi-driver studies, where multiple drivers need to interact with each other in one virtual environment, the probability of performing a successful study is even lower, as the behaviour of the human drivers cannot be fully controlled. While [Oel15b] already proposed guidelines for the creation of such scenarios, this paper describes how the probability of success can be monitored and even enhanced during scenario execution. Therefore, it describes an approach where the probability of success is modelled and where the scenario is dynamically adapted to provide higher rates of success.*

Keywords: *multi-driver studies, scenario design, Bayesian networks, probability estimation*

Introduction

Performing psychologically motivated driving simulator studies can be challenging. Scripts have to be implemented which describe the behavior of road users and active infrastructures, while several requirements have to be fulfilled. First of all, the scenario must be *realistic* in order to be transferrable into real life. Second, it must be *reproducible*, so that comparable results can be achieved in several runs. Third, the scenario needs to be *resilient*, as it has to cope with various behaviors of the drivers. Several other requirements may be added to this list according to the study to be performed. The resulting scripts mostly contain direct actions, i.e. changes of the behavior triggered by conditions related mostly to the human driven vehicle, like e.g. a virtual pedestrian jumping onto the street just in front of the human driven vehicle. Nevertheless, scenarios get more and more complex, as many actors have to be controlled, and as cooperative advanced driver assistance systems (ADAS) are tested which influence the behavior of the surroundings. Two years ago, we proposed to investigate new ways of scenario design in order to cope with this rising complexity [Sch14]. This is especially true when a multi-driver simulation is used where simulators are linked and two or more human drivers are participating in the same virtual environment. Examples of such studies can be found in e.g. [Hee12, Oel15a, Müh11].

In these studies, human drivers mostly have to interact with the simulated environment when at (at least) one point there is an interaction with one or more other human controlled vehicles. Therefore, a multi-driver scenario includes all individual interactions with the computer operated actors while it is also in control of the overall situation of each human driven vehicle. This is very important, as most of these scenarios are only successful when all human driven vehicles passed all interactions and scenes as desired, individually and with respect to each other. Esp. the latter increases the complexity, as the behavior of the individual human drivers has to be influenced when they do not behave as desired.

Example: Two human controlled vehicles have to drive different ways through a complex urban area, including various interactions with computer operated actors. After a while of driving, both vehicles are supposed to meet each other on an intersection. If one vehicle in this example is too fast or slow, this may already have an effect on the interactions with the computer operated actors, but robust scenarios will be able to cope with that by directly instructing the involved computer operated actors. The bigger issue will be that the human driven vehicles are not going to meet on the intersection, and that direct influencing, like commanding the human driver to change the driving behavior (e.g. by verbally commanding “go slower”) or strong narrowing of driving options (e.g. by placing computer controlled vehicles around the human driven vehicles) may conflict with the study’s requirements. The introduction of additional tasks for the drivers like keeping a given distance to leading vehicles or keeping a given speed is sometimes not applicable for studies or the realization is too complex. Therefore, the only possible solution would be to influence the human driven vehicles in a more indirect way.

In the following, a new methodology is shown which makes it possible to calculate the probability of success of a study. Further, it is shown how this information can be used to increase this probability by using indirect influencing measures, esp. focusing on multi-driver scenarios.

Successful scenarios

Ulbrich et al. [Ulb15] defined the terms “scene”, “situation” and “scenario”. They concluded that a scenario “describes the temporal development between several scenes in a sequence of scenes” and that “actions & events as well as goals & values may be used to characterize this temporal development in a scenario”. Following this approach, Fig. 1 shows two scenes which are supposed to happen after each other in an example lane change scenario, represented by the red line.

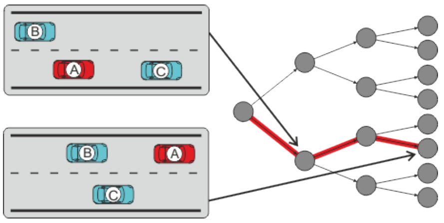

Figure 1. Two example key scenes (on the left) being part of a scenario (red line), which is a sequence of key scenes (nodes) and actions/events (edges). Adapted from [Ulb15].

A scenario therefore can be modelled as graph, or more precisely and due to the temporal order of scenes, as directed acyclic graph. A scenario with a single human driver always has one initial scene, where the simulation is started. The granularity of the upcoming scenes can vary and depends on the requirements of the overall study. In this paper a scenario consists of all *key scenes* which are needed to create the desired behaviour.

Example: A lane change scenario requiring the usage of an indicator would be described as at least three consecutive nodes: (1) the scene at the beginning, (2) the scene after setting the indicator, and (3) the scene after changing the lane. In contrast, a scenario where setting the indicator is optional would not include scene (2).

Key scenes always define required states for all involved agents (i.e. vehicles, pedestrians, traffic lights, ADAS, etc.) to different extent. Some agents will be fully defined in some scenes (e.g. the human driven vehicle at the initial key scene with a defined type, velocity, position, etc.), but sometimes the definitions cover only parts of the parameters.

A scene is transitioning to another scene by actions and events occurring in between. Actions can be triggered proactively, or reactively as response to events (e.g. goals, values or behaviour of other road users). The latter is often used in scenario design, when an action is triggered e.g. after a vehicle passed a well-defined position on the track or when a given amount of time has passed.

Using this definition, a scenario is successful, when all desired key scenes occurred in the needed order, i.e. when the complete directed path from the graph’s initial scene (i.e. the root node) to the targeted scenario ending scene has been visited.

Vice versa, when at least one key scene is missed, the scenario is classified as unsuccessful.

Probability of Success

When the probability of success of the overall scenario has to be calculated, we propose to do this by adding probability values to each node/key scene in the graph. Each probability value then indicates how probable a single key scene is, meaning that all involved agents in this scene are in the desired state. The probability value of a node is depending on the probability values of all of its states, of the predecessor node and on the individual probabilities of the actions and events located on the edge between the predecessor node and the node itself. Both can even include conditional probabilities, so that the overall scene probability is calculated like a Bayesian Network (see Figure 2).

In the former lane change example, the probability of scene (3), where the vehicle is on the left lane, is depending on the probability of being on the right lane before and the probability of the occurrence of the action of the lane change. The probability of a lane change is rising, when the driver makes use of the indicator (conditional probability).

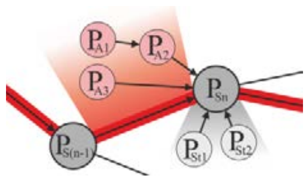

Figure 2. Example Bayesian Network for scene *n*, where the probability of the scene itself (P_{Sn}) is depending on the probabilities of its states ($P_{St1,2}$), its parent scene ($P_{S(n-1)}$) and some actions ($P_{A1..3}$)

The probability values are changing over time, as the scenario progresses through the key scenes. The key scenes will be reached one by one. In case of a miss, the scenario execution can be interrupted as it cannot be successful anymore.

The occurrence of actions and events will become more or less probable over time, depending on the driving style of the human driver. Therefore it is important to monitor the driving style of the human driver all the time in order to be able to classify his/her behaviour and to estimate the probabilities.

Example: An experienced car driver is supposed to follow an urban road in a driving simulator study, where 50 km/h is the speed limit. The surrounding traffic drives at this speed, there are no other obstacles, and the driver already spent some time in the driving simulator. The upcoming key scene is located kilometres away, requiring a vehicle speed of 45-55 km/h. When the driver is driving consequently faster or slower, the probability of success for the upcoming key scene will fall.

In literature, different methods are already existing (e.g. [Pla13]) which allow the prediction of velocity profiles of road users even in more complex situations, like at intersections or when including lead car behaviour. The probabilities of other actions or events may be predicted by using or adapting other methods like e.g. methods for manoeuvre classification [Gin10], driver's intent in urban areas [Lie12] or generally [Dos11, Sat15]. In general, these methods can be simplified for the use case of driving simulator studies, as various parameters are well-known or can – in case of surrounding road users – even be chosen in a supportive way, e.g. the affordance of a lane change on a highway and hence its probability can be supported by a braking lead car and a free left lane. Nevertheless, this paper does not aim at the procedures of the single probability estimations, but focusses on the general methodology of using and combining the probabilities instead.

A new dimension for multi-driver scenarios

Now the model-based approach is enriched by multiple drivers or road users. Multi-driver scenarios basically consist of at least two separate simulators, and each driver is following his/her own scenario. We distinguish between three *classes of multi-driver studies*: (1) The study consists of completely separated scenarios, where the drivers will never meet (e.g. just to enhance the quality of the study as drivers in single driver simulations tend to behave differently than in the outside world, as they know that all the other drivers are only animated [Oel15a, Jah10]). (2) The study consists of scenarios with at least one single interaction point, where the drivers are supposed to interact with each other for a short moment. (3) Scenarios including a continuous interaction between drivers for a longer duration, like two vehicles being part of a platoon.

Using the approach of representing a scenario as a graph, all of these different classes of scenarios can be represented by adding one scenario graph per driver, which effectively adds one dimension per driver. Whenever the drivers interact with each other, the corresponding key scenes will be part of each single driver scenario sub-graph. A typical *class 2* multi-driver study with a single interaction point is shown in Figure 3.

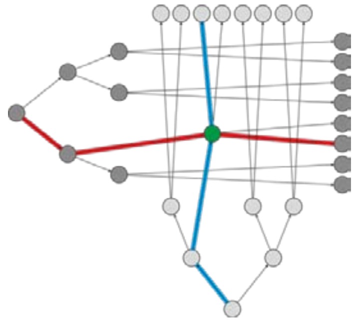

Figure 3. Example of a scenario graph of two drivers, which are supposed to follow separated scenarios (red/blue line) while meeting at one point in the scenario (green node)

The approach for calculating the scenario success can now easily be adapted to multi-driver scenarios, as the success of one interaction scene will simply depend on the probabilities of actions, events and predecessor key scenes of all related drivers.

Enhancing success of multi-driver scenarios

Now that success of multi-driver scenarios is calculable the question is how this information can be used to enhance it. Focussing on *class 2 multi-driver studies* with singular interactions of drivers at precise positions (e.g. on intersections, acceleration lanes) in the virtual world, the main risk of a scenario failure is that different drivers are not driving with the considered speed and therefore will miss each other in the relevant key scene.

According to this, the scenario success is directly linked to the probability of meeting each other at the target position. This probability depends on the arrival time of the drivers and therefore on the progression of their vehicles in relation to the distance of their vehicles to the interaction point along the proposed route. The progression of the vehicles depends on the parameters of the road network (e.g. narrow curves, highway), the behaviour of the surrounding road users (including the traffic flow), and the phasing of the potentially available traffic lights. Thanks to the fact that a driving simulation is used, all of those parameters are well-known and can be adjusted as long as the adjustments are not interfering with the restrictions of the study or with other key scenes.

In our approach, a simple velocity estimation algorithm is used for the calculation of the arrival time of each human driven vehicle at the desired position. It uses the road information (including speed limits, curvature etc.), parameters of the leading vehicle, traffic light phases and the current vehicle speed as inputs. In a first cycle standard values from literature are used, e.g. from [Sat16, Ken09], to estimate reaction times after traffic light phase changes, default longitudinal and accepted lateral accelerations and car following parameters like time headway and time-to-collision. These values are taken to calculate an initial assumption of the arrival time at the interaction point. Figure 4 gives an example overview on the velocity calculation around a traffic light. When the scenario has started, the mean difference between the current speed and the speed limit, as well as mean accelerations and reaction times are consecutively recorded and used to update the prediction of the arrival time with more accurate values.

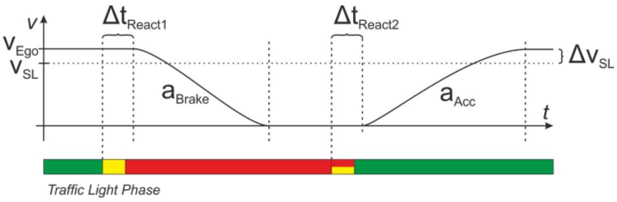

Figure 4. Velocity profile for the estimation of the arrival time of a vehicle at an interaction point. $\Delta t_{React1,2}$ are the reaction times after traffic light phase changes. Δv_{SL} is the mean deviation of the speed limit v_{SL} to the human driven speed v_{Ego}. a_{Brake} and a_{ACC} are the mean accelerations.

Whenever the predicted values of one vehicle does not comply with the equally calculated value of the vehicle supposed to be met, the scenario has to react dynamically. In general, such dynamic reactions must be performed carefully and indirectly, in line with the restrictions of the study. Possible dynamic reactions may include: (1) changed timing of traffic lights, (2) changed behaviour of surrounding vehicles, like e.g. slower leading vehicles or congestions, (3) planned detours, (4) changes in the environment like changed speed limits, weather conditions or even enlarged or shortened tracks (in case the virtual track is changeable online), (5) visual effects like showing a slightly modified speed in the speedometer or even changing the frustum values.

As the dynamic reactions can be seen as scenario alternatives, they can be included in the scenario graph as nodes with probabilities. The alternatives may also be combined, e.g. by using a detour, a slow lead vehicle and changing traffic light durations. During scenario preparation, the possible *catalogue of alternatives* has to be defined so that the scenario software is able to prioritize the alternatives and to choose the most suitable one in line with the scenario restrictions. The overall procedure is as follows: (1) The driving durations along the respective routes are calculated for each human driven vehicle as described before. (2) By calculating the deltas of the durations of all involved drivers the software knows how much each vehicle is delayed when arriving at the interaction area. (3) Whenever these delays exceed a given threshold, alternatives are calculated for the vehicles according to the *catalogue of alternatives*. (4) The best alternative (resulting in the smallest delay) is chosen and directly executed.

Figure 5 shows an example: Two human driven vehicles (E_1 and E_2) are starting to drive on separated roads (t_1) and are supposed to meet at a merging situation at the end of the scenario (t_6). Already after a few meters, E_2 is measurably slower than E_1. As the way to go still is long, the scenario software decides to command a detour for E_1 at t_2. Nevertheless, there again is a noticeable delay of E_2 at t_3, leading to a changed traffic light phasing at the upcoming intersection. E_1 gets a longer waiting time, while E_2 gets a green light. Prophylactically, the scenario software also decides to introduce a lead car to E_1, which is going to drive ahead of E_1 in a larger distance. At t_4 it becomes necessary to intervene again, so the lead car of E_1 is decelerated a little. After some minor corrections at the last traffic light (t_5), the scenario successfully ends at t_6.

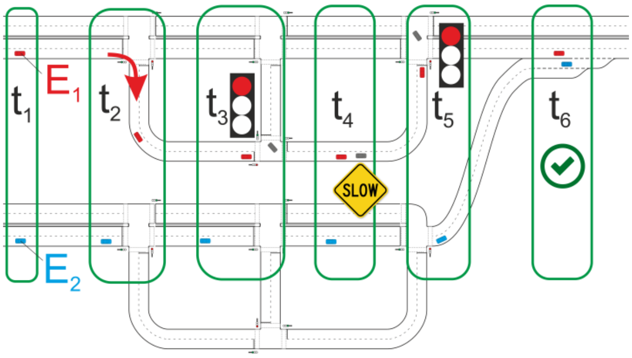

Figure 5. An example multi-driver merging scenario with two human driven vehicles E_1 and E_2 and different dynamically chosen alternatives to enhance the scenario success

The general procedure of calculating the success of the overall scenario and its key scenes, and the provisioning of alternatives can also be applied to the other classes of multi-driver scenarios as well as to single driver scenarios.

Conclusion

Complex scenarios and esp. multi-driver scenarios tend to be unsuccessful when drivers do not behave in a way foreseen by the scenario designers. In this paper, a method has been shown which enables scenario software to dynamically react to unforeseen situations by presenting and executing alternatives dynamically. It has been shown how these alternatives can be used to enhance the probability of success, esp. when focussing on multi-driver studies with singular interaction points of the human driven vehicles.

The method is currently implemented at the “Modular and Scalable Application Platform for ITS Components” (MoSAIC) Laboratory at DLR [Fis14] and will be used in future studies.

References

Doshi A. and Trivedi M. M. **Tactical driver behavior prediction and intent inference: A review** *14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2011, pp. 1892-1897. IEEE

Fischer M., Richter A., Schindler J., Plättner J., Temme G., Kelsch J., Assmann D., Köster F. **Modular and scalable driving simulator hardware and software for the development of future driver assistance and automation systems** *New Developments in Driving Simulation Design and Experiments*, 2014, DSC2014

Gindele T., Brechtel S. and Dillmann R. **A probabilistic model for estimating driver behaviors and vehicle trajectories in traffic environments** *Proc. 13th International Conference on Intelligent Transportation Systems (ITSC)* IEEE Conf, 2010, pp. 1625–1631.

Heesen M., Baumann M., Kelsch J., Nause D. and Friedrich M. **Investigation of cooperative driving behaviour during lane change in a multi-driver simulation environment** *Human Factors and Ergonomics Society (HFES) Europe Chapter Conference*, 2012, Toulouse, France.

Jaho E., Karaliopoulos M. and Stavrakakis, I. **Social similarity as a driver for selfish, cooperative and altruistic behavior**. *IEEE International Symposium on “A World of Wireless, Mobile and Multimedia Networks” (WoWMoM)*, 2010, IEEE, 1–6.

Kennedy, J. and Sexton, B. **Literature review of road safety at traffic signals and signalised crossings** (No. 436). 2009

Liebner M., Baumann M., Klanner F. and Stiller C. **Driver intent inference at urban intersections using the intelligent driver model** *Proc. IEEE Intelligent Vehicles Symp.* (IV), 2012, pp. 1162 – 1167.

Mühlbacher D., Zimmer J., Fischer F. and Krüger H. P. **The multi-driver simulator – a new concept of driving simulation for the analysis of interactions between several drivers** *Human Centred Automation*, 2011, pp. 147-158.

Oeltze, K. and Dotzauer, M. **Towards a best practice for multi-driver simulator studies**. *Workshop on Practical Experiences in Measuring and Modeling Drivers and Driver-Vehicle Interactions at AutomotiveUI’15*, 2015, Nottingham, UK.

Oeltze K. and Schießl C. **Benefits and challenges of multi-driver simulator studies** *IET Intelligent Transport Systems*, 2015, 9(6), pp. 618-625.

Platho M., Groß H.-M. and Eggert J. **Predicting Velocity Profiles of Road Users at Intersections Using Configurations** *IEEE Intelligent Vehicles Symposium* (IV), June 23-26, pp. 945-951, 2013, Gold Coast, Australia

Satzoda R. K. and Trivedi, M. M. **Drive analysis using vehicle dynamics and vision-based lane semantics** *IEEE Transactions on Intelligent Transportation Systems* 16(1), 9-18, 2015, IEEE.

Schindler, J. and Hesse, T. **Coping with Complex Driving Scenarios: Exploratory Scenario Design**. *New Developments in Driving Simulation Design and Experiments*, 2014, DSC2014, 97-104.

Ulbrich S., Menzel T., Reschka A., Schuldt F. and Maurer M. **Defining and Substantiating the Terms Scene, Situation, and Scenario for Automated Driving** *Proc. 18th Conference on Intelligent Transportation Systems (ITSC), 2015,* pp. 982-988, IEEE.