Using Geodata for Simulating Urban Traffic – Current Research in the Field of Traffic Engineering and Control

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1 Introduction

Daily mobility has manifold appearances, especially in urban environments. Numerous modes of transport, different types of traffic participants and differing travel demands and supplies occur within often restricted urban infrastructures. One key for understanding these complex phenomena is the representation of not only space and time, but also of the interactions of different traffic participants with each other and the specific traffic control. We are able to represent recorded trajectories of traffic participants, traffic light signals and traffic measures, together with urban infrastructural elements. From this data input, we can conduct microscopic traffic flow simulations, which may deliver further insights into complex urban traffic. Modelling and simulating vulnerable road users is challenging due to frequent movements on not assigned paths and disobeying traffic rules (red light violations). Therefore, higher quality geodata is crucial for the traffic flow simulation quality and its possible visualization in physical vehicle and bicycle simulators.

2 The usage of geodata in the transportation domain – focus on mapping and modelling the urban environment

Starting from modelling the transport infrastructure, the respectively used geodata has crucial importance on analyses and simulation outcomes in various spatial and temporal scales. Besides this, dynamic spatiotemporal information such as trajectories of traffic participants or traffic light states serve for modelling and simulating microscopic traffic flow. As an extension, we can validate our simulation results within simulator studies, and, extend this approach towards a selection of tools for active mobility research, which implies the inclusion of simulator study test subjects and the resulting qualitative and quantitative data.

2.1 Modeling static and dynamic components of urban traffic – transport infrastructure and trajectories of different traffic participants

Modeling static and dynamic components of urban traffic can start with traffic observations. Knowledge on partitions of traffic situations can already serve as an input for calibrating a model of microscopic traffic flow. Most of the accessible traffic information should imply a spatial component, of single positions of inductive loops, sequences of positions from GNSS positioning devices or of fixed positions, angles and heights when using video devices.

TWADDLE et al. (2014) use automated video analysis for the evaluation of bicycle movement and interaction. The sensors providing these videos might be RGB cameras installed at various fixed locations within the urban environment, favorably at buildings showing a visible road intersection. Via procedures coming from image processing and computer vision, we are able to extract every trajectory with the additional attributes speed, acceleration and road user type. Subsequently the data can be georeferenced and post-processed for enriching the trajectories with available infrastructural information as pictured in Figure 1.

Fig. 1:
Trajectories of vehicle drivers, bicyclists and pedestrians at one road intersection in Munich.

Starting with analyzing the data in Figure 1, we can, at a certain state, distinguish between typical, frequent and unusual travel behaviors of every type of traffic participant. The modelling of these behavior comes together with compromises to the used software and to the achievable complexity of implemented models. This continues until modelling specific interactions between traffic participants, traffic signaling, and, even predictions resulting from them. TWADDLE & BUSCH (2018) for example are proposing promising models for predicting responses to red signals, together with predicting the type of left-hand turns. Nevertheless, predicting infrastructure selection and the direction of travel are difficult.

It is possible to integrate external models in SUMO (TWADDLE, GRIGOROPOULOS & BUSCH 2016). This guarantees the modelling of complex urban traffic more precisely. After extracting or modelling static transport infrastructure, we include traffic light signaling, flows and assigned road segments with this software before performing the first simulations (LOPEZ et al. 2018, BEHRISCH et al. 2011, KRAJZEWICZ et al. 2012).

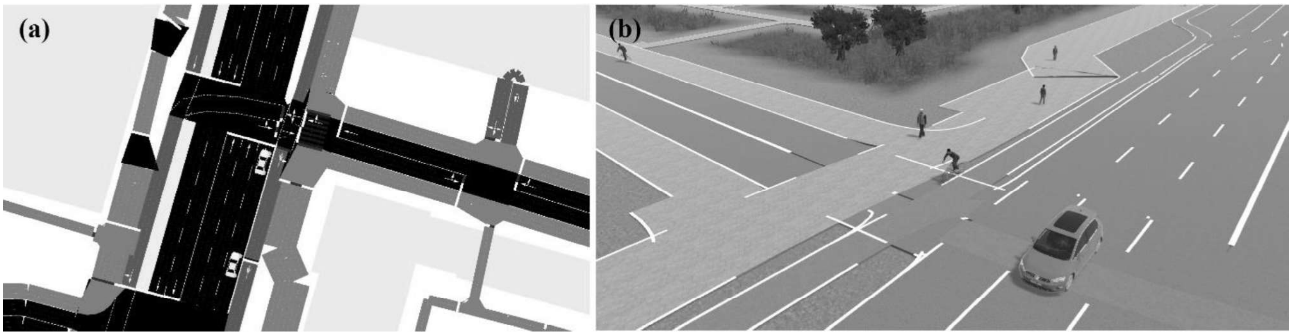

Fig. 2: Modelling process of (a) the road network in SUMO, and, (b) its subsequent representation in 3D after converting into the OpenDRIVE format.

As pictured in Figure 2, we are not only converting the transport infrastructure (Figure 2a) into its 3D representation in the OpenDRIVE format (OROZCO IDROBO 2015) via the software DYNAanimation[1] by TESIS (Fig. 2b), but also translating maneuvers of other traffic participants and states of traffic light signals. Translating infrastructure and traffic situations into representations resembling our perceived environment is the base for conducting our current bicycle simulator studies (KELER et al. 2018). The base for guaranteeing realistic traffic flows of vehicle drivers, bicyclists and pedestrians is applying a calibration and validation step that might use the most recent traffic information as coming from video observations (Fig. 1) or recorded traffic light signal, as it is for our cases coming from the city of Munich.

2.2 Simulating vulnerable road users – importance of bicycle traffic and pedestrian areas

Modeling and simulating microscopic traffic flow is not only a possibility for understanding traffic-related problems or evaluating the implemented traffic control strategies, it can also serve as a tool for planning the installation of additional and novel infrastructural elements, such as bicycle highways (FGSV 2014). By modifying widths and ordering of bicycle lanes, together with redesigning every affected road intersection, it is possible to test similar or varying flows of bicyclists together with variation in delays, congestion lengths and stop times. By varying bicycle type compositions, traffic conditions and traffic control strategies, we can evaluate the possible effect of installing bicycle highway infrastructure within complex built urban environments. Measures for evaluating the infrastructural modifications, as pictured with the two networks in Figure 3, can focus on traffic safety and traffic quality. One important component within the whole procedure is modeling the behavior bicyclists (TWADDLE, SCHENDZIELORZ & FAKLER 2014), together with respective speed, acceleration, and deceleration (TWADDLE & GRIGOROPOULOS 2016).

As pictured in Figure 4b, it is possible to visually investigate 3D representations of simulated traffic through a variety of sensors. The possibly 2 most common sensors of a Bicycle Simulator are speed and steering (KELER et al. 2018). Design and hardware selection for a bicycle simulator may imply many different sensors that guarantee different accuracies (DIALYNAS, HAPPEE & SCHWAB 2019), always depending on the implemented movement model for the bicycle simulator application (LEE et al. 2017). Depending on the latter we can guarantee more or less realism or accuracy in whether animation or usability. From the early 2000s until the late 2010s there has been numerous research on different bicycle simulators used as tool for analyzing various traffic-related aspects (KWON et al. 2001, HE, FAN & MA 2005, YIN & YIN 2007, SUN & QING 2018, SCHRAMKA et al. 2018).

Another approach in including realistic appearance of complex urban traffic is acquiring trajectories from video observations as pictured in Figure 1 and Figure 4a. This is apparently an ever growing popular application, when perceiving image processing and computer vision as the associated research fields. One example is the company DataFromSky[2]

[1] https://www.tesis.de/dynaanimation/

[2] http://datafromsky.com/

serving numerous users with highly accurate trajectories from various differentiated (through classification) road users. Due to our current capacities of processing massive video data sets on the fly, we are able to link different observations through modern communication technologies. On the other hand, we can use this data for calibrating our modelled simulation networks.

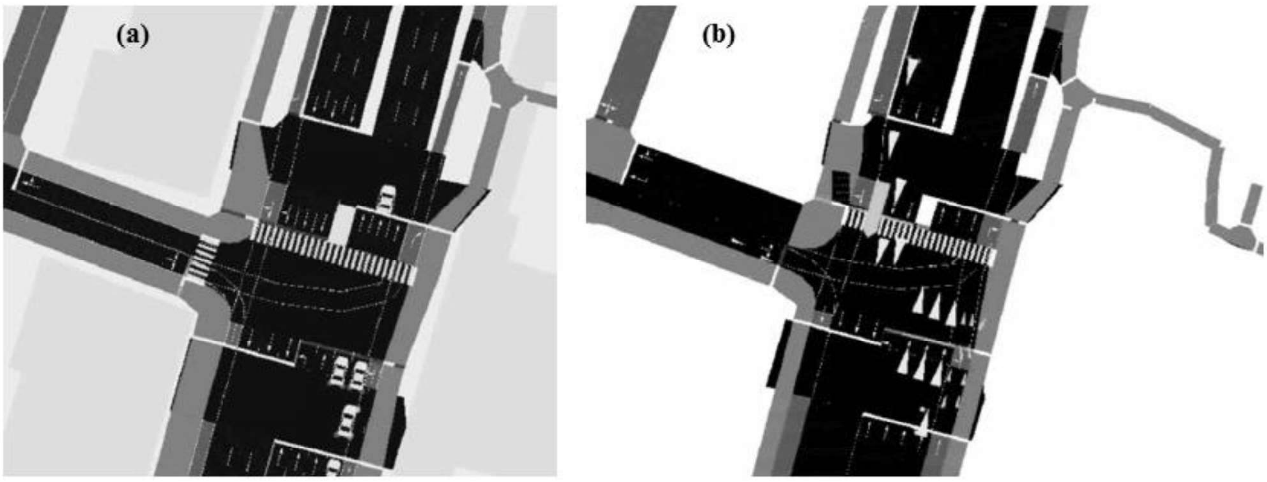

Fig. 3: Modelled road intersection at Ludwigstraße-Theresienstraße with (a) recent state of the infrastructure, and, (b) with modified traffic control and bicycle infrastructure.

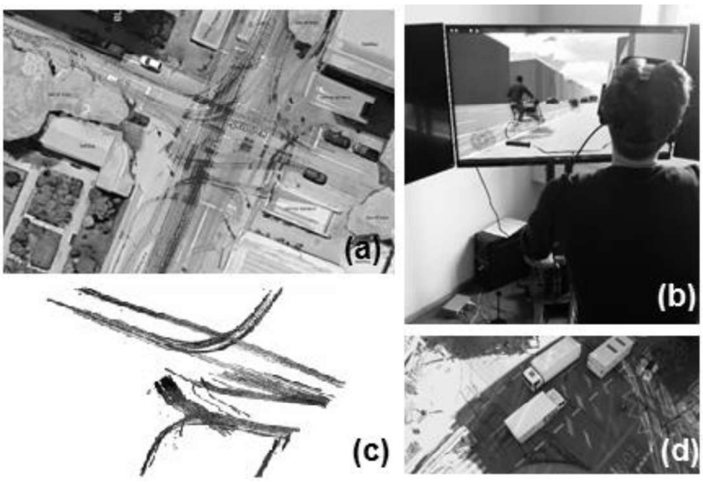

Fig. 4:
Tasks of trajectory extraction and video observation of modelled urban environments with (a) extracted conflict points between bicyclists and vehicle drivers from video trajectories of both traffic participants, (b) test subject following a designed bicycle highway at the modelled Ludwigstraße in Munich, (c) visualization of trajectory partitions of few frames of vehicle drivers and bicyclists at a mixed traffic road intersection, (d) video frame of heavy goods vehicles interacting with other traffic participants at a non-signalized intersection in Munich.

Resulting from the extracted trajectories, we are able to model the interaction between bicyclists and vehicle drivers as it is pictured in Figure 4c with the relation of vehicle and bicycle trajectory partitions of several frames. Besides the temporal selection, there is one important spatial component within every trajectory. Depending on the instantaneous velocities, movement directions and shapes of maneuvers, we are able to infer fields of view for every recorded trajectory. This is one of the most important attributes when inspecting interactions of traffic participants, and, the most important, when observing communication between every traffic participant. One option for evaluating the gained knowledge of timestamped visible spaces is the observation of specific maneuvers via VR glasses, as pictured in Figure 4b. For this option the field of view can be recorded directly and used for matching visible (moving) objects. This might also facilitate the, often expensive, computing of visibility polygons or volumes for every traffic participant. One bicycle rider or pedestrian might be influenced by numerous heavy-good vehicles that appear as fences at an urban intersection as pictured in Figure 4d. Assessing the visible parts in space might appear easier within a VR environment with this situation simulated at a bicycle simulator.

Besides assessing various traffic situations based on calibrated and validated simulation networks (with data on traffic flows and traffic light signaling), we can imply more usability into our case studies. This is due to evaluating novel traffic control signal displays via comparable test rides as for example the evaluation of different countdown timer displays for bicyclists as pictured in Figure 5. In this case study the comparability of results is more important than interacting with simulated traffic, as test subjects have to experience the same situations at specific positions of their trips. This is technically being realized via spatial trigger that do not only trigger the remaining countdown seconds and traffic light durations at specific locations, but also trigger predefined movements of other traffic participants.

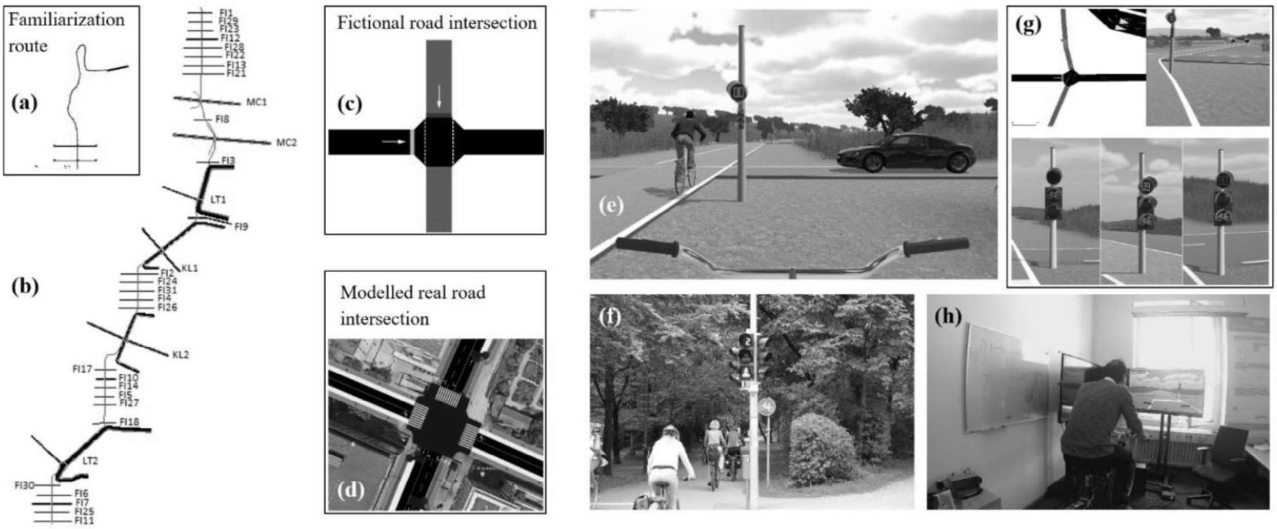

Fig. 5: Specifications of the first experiment for evaluating countdown timer displays with (a) familiarization route, (b) whole route with 33 road intersections, (c) fictional road intersections, (d) modelled real road intersections, (e) resulting bike simulator visualization via DYNAanimation, (f) one installed countdown timer display in Munich, (g) respective visualizations of the ego vehicle via SumoConnect function between SUMO and DYNAanimation and available countdown timer displays and traffic lights, and, (h) test subject using the bike simulator.

2.3 Further applications – active mobility research and geodata for traffic emission modelling

The flexible usage of massive trajectory data from video observations, its usage for calibrating different network representations, and, the simulation of three different modes of traffic might serve as an extendable workflow for improving simulator studies. Moving away from inspecting user experience of triggered traffic signals and road users, we focus on experiencing simulated traffic and its perception by different test subjects. Besides novel approaches for simulator test data collection such as recording eye movements, gesture detection and field of view estimations, there are several possible extensions that result from varying the introduced workflows. One important variation is the inclusion of additional modes of transport that rely more on dynamic developments and trends, such as the users of Segway Personal Transporters, E-Scooters and Skateboards, together with respective changes of modes, which appear frequently within complex and busy urban environments of today's cities. This new perception of urban traffic is a challenge for classification and realistic simulation. Nevertheless, it is important to include the analyst as a participating part of physical simulators that allow additional qualitative evaluation of simulative results.

Besides these approaches that might support getting more insights into the connection between perceiving complex urban space and complex traffic situations, we are able to include further georeferenced data into our analyses. This can support knowledge discovery on unusual correlations as the connection of bicycling quality and traffic emissions. Traffic simulation can also be the starting point of traffic emission modelling. So et al. (2017) propose an integrated simulation approach for estimating emissions based on more reliable vehicle performance measures. It consists of a microscopic traffic simulation model, a vehicle dynamics model, and, an emission estimation model.

Another field of applications consists of introducing location-based services for traffic participants that might increase traffic efficiency and traffic safety, as the Sitraffic SiBike application for bicyclists (Grigoropoulos et al. 2018)

While selecting suitable data sources for relating further environmental aspects to traffic simulation results can be trivial, the semantic relations or possible matching strategies of this data to simulated traffic is often complex. This contributes to research on modelling complex urban relationships with various evaluation steps coming from different domains.

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