DECISION SUPPORT FOR DYNAMIC CITY TRAFFIC MANAGEMENT USING VEHICULAR COMMUNICATION

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Abstract: In this paper, we present an integrated simulation approach featuring centralized and decentralized traffic management in urban areas. Our aim is to improve traffic flows by dynamic traffic management which is supported by vehicular communication interlinking centralized and decentralized decision making. We focus on traffic state estimation and the optimization of traffic lights as a central component to influence local traffic states, while individual traffic participants' behavior is modeled by multiagent systems. Traffic participants achieve their individual goals by formation of groups and improving their knowledge about the road network by means of learning. Modeling of vehicular communication takes into account specific characteristics of urban areas, ensuring the realistic collection and dissemination of (de)centralized information.

We provide a comprehensive microscopic traffic simulation framework featuring innovative functionality regarding dynamic traffic management, decentralized decision making as well as realistic communication modeling. To illustrate and validate our approach, we present a use case in a city scenario. Simulations are implemented based on the microscopic traffic simulator AIMSUN, which is significantly extended using the AIMSUN API.

1 INTRODUCTION

The 21st century will be a century of urbanization, since cities provide more attractive opportunities for employment, education, cultural and sports activities. However, increasing traffic flows within limited city space lead to negative effects in terms of emissions and traffic jams.

Dynamic traffic management in cities may be the key for efficient control of urban traffic flows. It refers to a broad concept which aims at the collection of traffic data and the real-time control of traffic flows by dissemination of traffic information. Most approaches follow a *centralized perspective*, which is based on data collection and information processing in centralized traffic management centers. Here, traffic control strategies are usually designed area-wide.

The centralized approach requires a large amount of information to be transmitted to control centers in the form of network data and back in the form of control actions. This requires a very powerful and reliable communication network infrastructure. In the case of a network failure the centralized management becomes unavailable.

The alternative approach to centralized traffic management is the *decentralized* one. Here, traf-

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fic participants act according to local information, i.e. they optimize their behavior based on local data. This approach can be more cost-effective and robust against communication network failures.

In our work, we focus on the combination and alignment of centralized and decentralized traffic control methods in order to improve the efficiency of traffic management. Vehicular communication serves as a fundament for the linking of centralized control strategies and traffic participants. Decentralized decision making is investigated in terms of multiagent systems. We examine the alignment of centralized and decentralized traffic control by an integrated simulation of city traffic, communication and multiagent modeling. This paper focuses on the required methodology and the enhancement of a traffic simulation environment that corresponds to these requirements. First results illustrate the necessity of an integrated approach.

This paper is organized as follows. Section 2 describes role and tasks of dynamic traffic management. Fundamentals of decentralized decision making with respect to multiagent systems are discussed in Section 3. Basics of modeling and simulation of vehicular communication are presented in Section 4. The integration of methods in a simulation environment, the description of a use case and preliminary results are shown in Section 5. Finally, Section 6 concludes this paper.

2 DYNAMIC TRAFFIC MANAGEMENT

In urban areas, infrastructure often presents a bottleneck due to traffic demands exceeding available road capacities. Here, dynamic traffic management is necessary in order to provide strategies for efficient control, e.g. by applying time-dependent signal plans considering the respective day of the week or hour of the day to incorporate the actual traffic situation.

The traffic load typically varies strongly throughout the day. Therefore an adaptation of the traffic management according to the actual demand is essential. Well-known dynamic traffic management solutions include variable traffic signs and variable direction signs at motorways. To enable dynamic approaches within urban areas, a detailed knowledge of the actual traffic state is essential (see Section 2.1). Furthermore, an optimization of traffic signal plans is required (see Section 2.2).

2.1 TRAFFIC STATE ESTIMATION

A fundamental requirement for every kind of traffic-dependent control is the availability of information about the actual traffic state. In the following, we focus on agent-based methods for traffic coordination and management to meet this challenge.

Within the work presented here we use the capabilities of communicating vehicles for traffic state estimation in terms of *level of service*, LOS (FGSV, 2001). By collecting messages which are created by vehicles equipped with communication systems at the traffic management center (TMC), we measure the mean travel time on a road segment. In particular, we compute the traffic state at every road (section) for each time interval (e.g. a cycle, every 5 minutes, etc.) according to the following algorithm:

1. Collect the timestamps $t_{in,i}$ and $t_{out,i}$ for the vehicle i entering and leaving a given road section.
2. Compute the mean real travel time t_{real}

$$t_{real} = \frac{1}{n} \cdot \sum_{i=1}^{n} (t_{out,i} - t_{in,i}),$$

   where n is the number of vehicles on a section.
3. Compute the ideal travel time $t_{ideal} = \frac{\ell}{v_{opt}}$, which is the time a vehicle would require to traverse the section during free, uncongested traffic (where ℓ is the section length and v_{opt} the optimal speed).
4. Calculate the mean delay time $t_{del} = t_{real} - t_{ideal}$.
5. Identify the LOS by using the classification of t_{del} according to the following table (FGSV, 2001):

$t_{del}[sec]$	<20	<35	<50	<70	<100	>100
LOS	A	B	C	D	E	F

2.2 OPTIMIZATION OF TRAFFIC LIGHTS

Dynamic traffic management can be realized by means of centralized and decentralized control. Using centralized control, data is collected in a traffic management center (TMC) in order to provide a consistent picture of the actual traffic state. Thus, goals like overall traffic quality and incident management can be pursued by implementing strategies via traffic infrastructure components. Using decentralized control, infrastructure elements like single traffic lights make simple local decisions which are usually not balanced with decisions made in the neighborhood.

The objective of traffic management systems is the use of information infrastructure to detect different states of traffic flow and to react accordingly in order to preserve or improve the supervised network's overall performance. In our work we combine a new dynamic traffic control approach, *reduction of intergreen times by elimination of phases and phase changes*, with well known procedures of traffic planning (signal plan adjustment (FGSV, 2010)) and traffic control (signal plan transition (Shelby et al., 2006)).

Determination of Nonessential Phases

A signal plan consists of phases and phase changes. The duration of the phase change is determined by the decisive intergreen time, i.e. the longest intergreen time among all combinations of ending and starting signal groups.

A recent study shows that there is a potential of a capacity increase up to 7 % by reducing intergreen times and thus phase change times (Boltze and Wolfermann, 2011). To reach this potential, a precise computation method for intergreen times compared to the state of the art (FGSV, 2010) is needed. Another way to reduce intergreen times is the elimination of one or more phases and corresponding time-consuming phase changes. Using this approach, the validity of the remaining signal plan has to be assured: There has to be either a green time or a close alternative route for every traffic participant.

We test every possible phase to be eliminated from the signal plan. For this purpose we

- eliminate a phase from the actual signal plan and in doing so eliminate some corresponding turnings,
- check whether the new signal plan is valid (see above),
- determine an optimal signal plan and
- calculate the benefit.

The benefit of a new signal plan can be measured in terms of capacity increase or performance improvement (e.g. LOS improvement). At the end of this procedure, the best valid signal plan is chosen.

3 MULTIAGENT ORGANIZATION FOR DECISION SUPPORT

In this Section we describe the model of the vehicles' behavour on the individual level. Multiagent systems (MAS) constitute an appropriate and most commonly used model for decentralized systems modeling, including traffic systems. In (Fiosins et al., 2011) we presented a two-stage multiagent planning approach for vehicle agents in urban traffic: During strategic planning the vehicles plan their optimal routes, during tactical planning they make decisions about speed regulation and lane changes. The amount of communication between agents and the TMC should also be taken into account in order to make the model realistic.

3.1 INDIVIDUAL LEARNING

We begin with a description of the strategic planning (optimal route selection): The environment is represented as a sear graph $G=(V,E)$ (Bergenthal et al., 2004), where nodes V correspond to the streets, the edges E to the turnings, which connect these streets.

The strategic planning process of the agent j is based on its individual weights $c_j^{ind}(t)$, which correspond to the edges of G. We suppose that there are k classes of the agents, which differ by the route preferences (initial individual weights).

Each vehicle agent is equipped by a communication system, which allows it to receive the information from the TMC. It receives two types of the information: strategic weights $c^{str}(t)$ and actual travel times $c^{act}(t)$. The agent updates its individual weights as

$$c_j^{ind}(t+1)=U_j(c_j^{ind}(t),c^{tmc}(t)).$$

The function U_j can be a linear combination of a vehicle and TMC weights or act similar to Q-learning approach. According to the individual weights, the shortest path in the search graph is constructed.

In the following, we describe the tactical planning approach. According to its strategic plan, a vehicle agent enters a street and then learns how to use it.

The state $s^j(t)$ of the agent j is described by a tuple, consisting of a distance to the end of the street $x^j(t)$, lane $l^j(t)$, speed $v^j(t)$ and the time from the last traffic light repeat $u^j(t)$. Possible actions consist of pairs $a=\langle\Delta v,\Delta l\rangle\in A$, which correspond to speed and lane change. We assume that for each state $s^j(t)\in S$ a corresponding reward $r(s^j)$ is available.

We introduce a state-action value function $Q^j(s^j,a^j)$ (Sutton and Barto, 1998), which represents an average reward for the j-th agent, which starts from the state $s^j\in S$ and performs the action $a^j\in A$. Then for the state-action pair (s^j,a^j) and the next state s'^j, there exists the following recurrent equation:

$$\begin{gathered}Q^j(s^j,a^j)=Q^j(s^j,a^j)+\\+\alpha_j\left[r(s'^j)+\gamma_j\max_{a'^j}Q^j(s'^j,a'^j)-Q^j(s^j,a^j)\right],\end{gathered}$$

where α_j and γ_j are learning parameters.

3.2 GROUPING

Agents join groups (Song et al., 2007) in order to reach individual goals in a more efficient way by adjusting speed and possible lanes, like getting from A to B with a low travel time. Groups need to be motivated and are usually formed by common goals. For motivation of vehicle agents we use reward functions and the group rewards are defined to be higher than rewards for fulfilment of individual goals. Once a goal is adopted, an agent cannot drop it freely; the agent must keep the goal until it is fulfilled, unfulfillable or irrelevant.

Let $R(S,A)$ be the joint reward function for the joint state S and joint action A, which include all agents in the system. Let $\tau = \{\tau_1, \tau_2, \ldots, \tau_k\}$ be the set of groups and $R_{\tau_i}(S_{\tau_i}, A_{\tau_i})$ be the reward of the group τ_i, where the arguments S_{τ_i} and A_{τ_i} are the states and the actions of the group τ_i. Note that sometimes we write $R_{\tau_i}(S,A)$; in this case, the group reward function depends on the group agent states and actions.

The Difference Utility (Reward) concept (Agogino and Tumer, 2004) is usable in the case of partially observable domains.

We call the system *factored*, if the group rewards have the following property:

$$R_{\tau_i}(S,A) \geq R_{\tau_i}(S,A') \Leftrightarrow R(S,A) \geq R(S,A'). \quad (1)$$

In order to estimate the group formation efficiency, the difference reward function DR_{τ_i} for the group τ_i may be used. It is defined as

$$DR_{\tau_i}(S,A) = R(S,A) - R(S, A_{-\tau_i} + A^c_{\tau_i}), \quad (2)$$

where $A_{-\tau_i}$ is the joint action of the agents, not affected by the group τ_i, but $A^c_{\tau_i}$ is the joint action of the agents in the group τ_i, replaced by constant. Usually $A^c_{\tau_i}$ is taken as equivalent to removing the agents of the group τ_i from the system.

This investigation focuses on road networks and grouping is done on a sequence of regulated intersections on one (linear) road. The vehicles intend to pass several successive intersections without stops trying to minimize their individual travel times, whereas an optimal throughput in the network is desired by the centralized traffic management and traffic lights can be regulated accordingly. The idea is to create a preference for vehicles to join groups and act coordinated, in form of a "green wave" priority, which can be found in public city transport nowadays. In this way, an interaction between the centralized and the decentralized approach is created which is beneficial for both.

Another benefit of group formation is a simplified control: Only the whole group or the group leader has to make decisions, other group members only contribute to the achievement of group goals, performing only local optimization. Furthermore, information sharing between group members is possible.

4 VEHICULAR COMMUNICATION

Wireless communication between vehicles and their environment opens up a new dimension of innovative applications which will increase safety and comfort for the driver in the future. Possible network topologies include infrastructure networks (Vehicle-to-Infrastructure, V2I) as well as Ad-Hoc networks (Vehicle-to-Vehicle, V2V). However, in contrast to conventional wireless LANs, these topologies are highly dynamic and present a variety of challenges for wireless communication.

Multiagent systems are usually modeled independently from the underlying communication technology and corresponding models assume perfect information transfer between agents. However, the wireless channel causes limitations in terms of communication reliability and capacity which have to be considered as they are inherent to IEEE 802.11 wireless LANs. Therefore, we use a dedicated communication model for our investigations.

4.1 COMMUNICATION MODEL

In order to simulate large scenarios with a manageable complexity, we make use of the traffic simulator's API module to build our own communication model specifically for urban environments.

Application Model

We assume that vehicles are equipped with communication systems that periodically broadcast Cooperative Awareness Messages (CAMs) using a repetition interval of 500 ms. These CAMs contain status information (e.g. position, speed and driving direction) which is used to detect the presence of neighboring vehicles and to estimate the current traffic conditions without need for any additional traffic detectors.

Radio Propagation Model

Typically, wireless network simulators assume a generic propagation model, such as the *Free Space* or *Two-Ray Ground* reflection model. While the former is a completely idealized model, the latter considers the effect of earth surface reflection and can be more accurate. However, neither of them considers the effects of the surrounding topology on radio propagation, which is especially important in urban environments. Therefore, models which capture predictable shadowing effects are appropriate for modeling urban vehicular communication, where the effects of buildings should be taken into account.

In (Sommer et al., 2010), the authors present a computationally inexpensive simulation model for radio shadowing in urban environments based on real world measurements, which comprises an estimation of the effects that buildings have on the radio communication between vehicles. We combine their general model with a *Nagakami* propagation model for determining the received signal power level.

Based on the calculation of received signal power at each receiver, the arrived packets are determined to be successfully received or lost. Our model determines the received power P_r at a certain distance d:

$$P_r[\text{dBm}] = 10\log_{10}\left[X\left(m, \frac{P_{r,FS}}{m}\right)\right] - X_{obs}, \quad (3)$$

where $X(m, \frac{P_{r,FS}}{m})$ is a random variable following a Gamma distribution with shape parameter m and scale parameter $\frac{P_{r,FS}}{m}$ describing the *Nakagami* multipath fading component. $P_{r,FS}$ is the received signal power according to the deterministic free space path loss:

$$P_{r,FS}[\text{mW}] = P_t \frac{G_t G_r \lambda^2}{(4\pi)^2 d^\alpha L},$$

where P_t represents the transmission power, G_t and G_r the antenna gains and λ the carrier wavelength, d is the linear distance between transmitter and receiver, α the path loss coefficient and L a system loss factor.

The term X_{obs} in equation 3 describes the additional attenuation of a transmission due to an obstacle as introduced in (Sommer et al., 2010).

Medium Access Control Model

Vehicular communication relies on a wireless channel which is shared by all stations in the network, so access to the shared channel needs to be coordinated to avoid collisions. Medium access in vehicular networks is based on the carrier sense multiple access with collision avoidance (CSMA/CA), but is subject to some modifications, like communication without prior association or authentication with a basic service set (BSS) (ETSI, 2010).

As our communication model currently directly interacts with the AIMSUN API (see Section 5), communication modeling is restricted to AIMSUN's granularity of simulation time, which provides a minimum time step length of 100 ms, while frame durations and MAC timings in IEEE 802.11 are in the range of μs. Therefore the current version of the implementation does not model medium access and collisions yet.

5 USE CASE AND IMPLEMENTATION

In the following, we describe a use case comprising efficient routing in urban road networks by centralized and decentralized decision support. Communication ensures distribution of information required for centralized and decentralized decisions. We focus on the implementation of functionality which integrates traffic and realistic communication simulation.

The use case refers to the investigation of the impact of centralized and decentralized decision support during the morning rush hour within a part of the city road network of Hannover, Germany. Here, at least one junction is regularly overloaded, leading to traffic jams and significant extensions of individual travel times. Our aim is to automatically identify junctions suffering from bad traffic quality and dynamically adjust their traffic signal programs (see Section 2). Then, a centrally predefined rerouting strategy is selected and communicated to the individual vehicles, which may react to this new information and redefine their route through the network by taking into account their individual cognition of the traffic state (see Section 3). Thus, congestion at a crowded junction may be alleviated by spacious rerouting.

A model of the road network in the southern part of Hannover is implemented in the traffic simulation software AIMSUN. It allows detailed modeling of city road traffic in terms of road infrastructure, behavior of the vehicles, traffic light control etc., being embeddded in a microscopic traffic simulation. We parameterize traffic flows and traffic signal programs according to data from empirical traffic data collection as well as control programs being in operation. While AIMSUN features precise modeling of single vehicles, traffic lights and urban road infrastructure, the simulation of vehicular communication and decision making is not supported readily.

In order to establish decentralized decision support, a modular software architecture has been developed. Each vehicle has a navigation system, containing a graph representation of the road network, a communication module for reception and broadcasting of V2V and V2I messages, a set of applications used for decentralized decision making in terms of grouping as well as individual routing based on updated information by the centralized traffic management and a learning application which features continuous observation of the vehicle's anticipated and realized behavior and thus updates its knowledge about the network.

First simulation results allow insights into efficiency and applicability of the simulation framework. Figure 1 shows the effective number of nodes in the communication range of a specific node while it traverses the scenario when using a radio propagation model with and without consideration of obstacles. Results obtained are based on the above mentioned communication model (see Section 4). Compared to a model without obstacle consideration, which mainly depicts an ideal communication environment, a more realistic model leads to a significant difference of vehicles in communication range (at maximum: 145). This insight is crucial for agents' decision making, which usually assumes ideal communication and availability of information. In sum, the consideration of buildings significantly affects dynamic traffic management applications in city road networks.

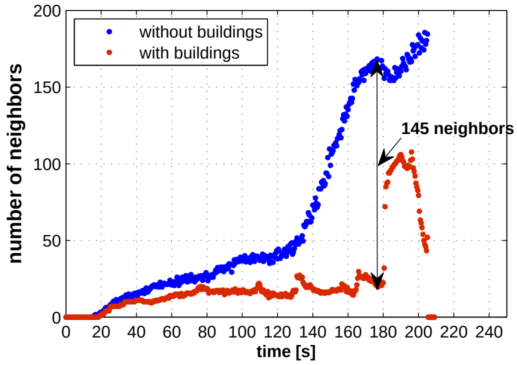

Figure 1: Mean number of neighbors with/without consideration of buildings

6 CONCLUSIONS AND FUTURE WORK

We have presented an integrated approach for simulation of central and decentralized traffic management in urban areas. Vehicular communication improves central and enables decentral decision making.

A microscopic traffic simulation tool has been enhanced by dynamic traffic management functionality, multiagent decision support and vehicular communication. First results show the importance of a realistic simulation model for analyzing (de)centralized traffic management in an urban context.

This paper presents work in progress. The architecture of the framework presented allows simple integration and investigation of future services for traffic participants. Applications may be investigated in terms of traffic performance, technology requirements and the reasonable level of centralized and decentralized control.

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