An Agent-based Approach to a Temporal Headway Development Statistics in Urban Traffic using Three-phase Theory

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Abstract: An automated vehicle is supposed to merge into the major street of a T-intersection, while disturbing the ongoing traffic as little as possible. At the same time, different requirements regarding its driving strategy have to be fulfilled with respect to safety, comfort and energy conditions. It is desirable to enable a fluent automated drive and to avoid stopping during the approach at all. We implemented an agent-based simulation using the Kerner-Klenov model in framework of the three-phase traffic theory. Using a high number of interacting vehicles leads to a multi-agent system (MAS). A normal distributed free flow parameter based on empirical traffic data is introduced and serves as an input parameter to the simulations. The simulations output yield temporal headway development-statistics, which enables a prediction of the traffic situation on the major street. This allows the automated vehicle to adjust its speed in preparation of merging into the best possible gap considering the above-mentioned requirements. Hence, taking these statistics into account helps to optimise the driving strategy of the automated vehicle.

1 INTRODUCTION

Automated vehicles are expected to play a major role in road traffic within the next decades. Thus, it is necessary to manage the oncoming heterogeneous traffic between classical and automated vehicles. Especially human behaviour represents a factor of uncertainty in this context. That is why we choose a statistical approach to make different driving behaviour as predictable as possible.

This work describes an approach that allows automated vehicles to interact with common road traffic in a safe and efficient way.

At first, an overview is given about the most important theories and agent-based models which are used to describe road traffic (subsection 1.1 to 1.3). Finally, subsection 1.4 describes the specific application.

1.1 Nagel-Schreckenberg Model

In 1992 Kai Nagel and Michael Schreckenberg came up with the idea of using cellular automata (CA) to simulate freeway traffic (Nagel and Schreckenberg, 1992). Using this microscopic approach, they were able to model a phase transition from laminar flow to congested traffic with increasing vehicle density.

Hence, the *Nagel-Schreckenberg model* distinguishes two phases of traffic (Kerner, 2017). Several advancements of the model were suggested since then; to name just a few: (Rickert, 1996), (Hafstein, 2004), (Chmura, 2014).

1.2 Three-phase Traffic Theory

However, in *three-phase traffic theory* (Kerner, 2004) one more phase of traffic is taken into account. The theory divides congested traffic into the synchronized flow phase S and the wide moving jam phase J by introducing a so-called synchronisation space gap g between consecutive vehicles.

The synchronisation space gap is a direct consequence of humans accepting different distances to the preceding vehicle as long as this gap is not getting smaller than the safe space gap g_{safe}. The safe space gap is related to the safe speed v_{safe} (Krauss et al., 1997). Due to the associated speed adjustment, the synchronised flow phase S is explained.

By contrast, the wide moving jam moves downstream through any other traffic phase, while

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maintaining its downstream front's mean velocity. This is the characteristic feature of phase *J*.

Last but not least, there is the non-congested traffic phase, which is called the free flow traffic phase *F*. It usually occurs when there is a low traffic density, i.e. when interactions between single vehicles are negligible. Consequently, they are free to choose their speed as long as it is in conformity with underlying road limitations like speed limits.

Usually, through an increase in density, e.g. at a bottleneck (Kerner, 2000), a phase transition from free flow *F* to synchronized flow *S* can occur.

The classical flow instability (Chandler and Herman, 1958) has been taken over by the three-phase traffic theory. Within Kerner's Theory, it is responsible for the spontaneous emergence of wide moving jams leading to a phase transition from *S* to *J*.

1.3 Kerner-Klenov Model

The related *microscopic* and *stochastic* model version of the three-phase traffic theory is known as *Kerner-Klenov model*. Single vehicles are supposed to be the simulation's agents. Due to the high number of interacting vehicles, it is a multi-agent system (MAS). In this work, we use the model version that is discrete in space and time (Kerner and Klenov, 2009). All containing parameters and functions are adapted to urban traffic (Kerner, 2013). Although this model is not cellular automaton-based, some of its behaviour is quite similar to (Nagel and Schreckenberg, 1992). In addition, the used assumptions are based on empirical traffic data. As it is shown in Chapter 1, 2 and 4 in (Kerner, 2017), the model's underlying three-phase traffic theory is best suited to describe traffic.

For a detailed view on the underlying mathematics and the high complexity of the model, please see (Kerner, 2017).

The spatial headway g_n of a vehicle for time step n is defined as follows (Kerner, 2017):

$$g_n = x_{l,n} - x_n - d, \tag{1}$$

where x_n is the position of the vehicle, $x_{l,n}$ the position of its preceding vehicle and d the vehicle length including the mean space gap between vehicles that are in standstill. Furthermore, the *temporal headway* τ_n is obtained by dividing equation (1) by the vehicle speed v_n:

$$\tau_n = g_n / v_n = (x_{l,n} - x_n - d) / v_n \tag{2}$$

The time step of the simulation is always marked by the index n.

As mentioned above, vehicles being in the free flow traffic phase *F* are capable of choosing their speed largely free. The related parameter within the Kerner-Klenov model is called v_{free}.

1.4 Application

Usually, the Kerner-Klenov model is applied to analyse *macroscopic* properties like phase transitions at bottlenecks. The predictions made by the three-phase traffic theory are matching empirically observed traffic patterns (Kerner, 2017, pp. 73-81).

However, the present case is about a *microscopic* analysis of vehicle headway development and brings a new application to the model.

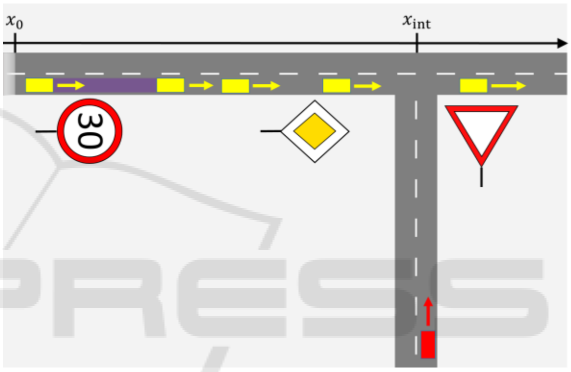

Figure 1: T-intersection with common road traffic on its major street (yellow boxes). An automated vehicle (red box) is approaching from below and tries to merge into the ongoing traffic (purple marked headway). The question is how the marked headway has developed, when reaching the intersection point x_{int}. There is a speed limit of 30 km/h. Within one realisation, all containing vehicles are initialised at x_0 using the same temporal headway τ_{init}.

The specific application contains a T-intersection (figure 1) without traffic lights but high numbers of common vehicles. An automated vehicle (red box) is approaching the intersection point aiming at merging into the ongoing traffic (yellow boxes). When the current traffic situation on the major street is provided to the automated vehicle, a statistical analysis based algorithm can predict the best gap for merging into the street. In terms of safety, comfort and energy conditions, the approach to the intersection should not be interrupted by a stop. That is why, it is necessary to carry out a statistical analysis of how the headway between two consecutive vehicles on the major street develops, first.

Following this guideline, we implemented a simulation based on the Kerner-Klenov model adapted to urban traffic using open boundary conditions. Within one simulation, all containing, identical vehicles were initialised at x_0 with the same initial temporal headway τ_{init}. Different simulations - with thousands of cars each - were realised by using the following values:

$$\tau_{\text{init}} = \{2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0\}\ \text{s} \qquad (3)$$

When the middle of the marked space gap in figure 1 reaches the intersection point x_{int}, the temporal headway is buffered. Whenever this condition is met, we call the set of the corresponding time steps $\widetilde{N}$. Doing so with a large number of cars enables a statistical evaluation. The related temporal headway τ_n is called

$$\tilde{\tau} = \tau_n | n \in \widetilde{N}. \qquad (4)$$

In this work, we choose the distance d_{int} between the point, where the cars are initialised x_0 and the intersection point x_{int} as 100 meters.

$$d_{\text{int}} = x_{\text{int}} - x_0 = 100\ \text{m}. \qquad (5)$$

The publically funded project “MEC-View” aims at collecting vehicle data from an urban major street using an infrastructure-based sensor system. Like in this work, the sensor system monitors approximately 100 meters of the major street. That is why this value is used for the parameter d_{int}. The collected data is provided to an automated vehicle approaching the concerned T-intersection. Using this information supports the automated vehicle to merge into the ongoing traffic.

2 RESULTS

2.1 Constant Free Flow Parameter

To our best knowledge, the Kerner-Klenov model is always used with a constant free flow parameter. This means in particular, that the same free flow speed v_{free} is assigned to all vehicles. Due to the speed limit on the current T-intersection, it is set to 30 km/h.

In figure 2, the concerning results are shown for the usual case (v_{free} = *const.*). Sharp peaks are resulting for the PDF, which reflects the temporal headway distribution. That means $\tilde{\tau}$ seems to stay practically constant within the distance $d_{\text{int}} = 100$ m and is not changing significantly. Thus, for the initial temporal headway applies:

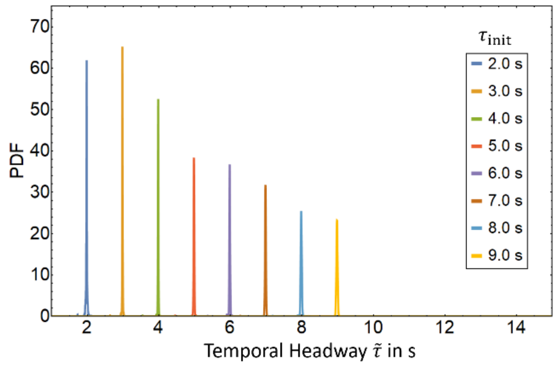

Figure 2: Probability density function (PDF) against the temporal headway $\tilde{\tau}$ at the intersection point x_{int} for different initial temporal headways τ_{init}. For the free flow parameter of each vehicle applies $v_{\text{free}} = 30$ km/h. All vehicles are initialised at x_0 (see figure 1). Due to only slight model fluctuations, sharp peaks are seen, i.e. the temporal headway is not changing significantly within the range from x_0 to x_{int} (100 meters).

$$\tau_{\text{init}} \approx \tilde{\tau} \qquad (6)$$

This fact is also confirmed by a very small variance in combination with an almost equal mean value (see Table 1). Because these results do not seem to be realistic, we present a collected empirical dataset in the following subsection 2.2 to justify a different approach in subsection 2.3.

Table 1: Mean, variance and skewness of the distributions shown in figure 2. Please note: due to the peak-like shape of the underlying distributions, the variance is specified in 10^{-5} s.

τ_{init} [s]	Mean [s]	Variance [10^{-5} s²]	Skewness [s³]
2.0	1.979	0.50	-3.69
3.0	2.981	0.41	-14.15
4.0	3.980	0.73	-14.75
5.0	4.979	1.33	-13.63
6.0	5.979	1.41	-14.97
7.0	6.978	1.98	-15.46
8.0	7.977	2.97	-13.94
9.0	8.997	3.57	-13.85

2.2 Free Flow Speed in Empirical Speed Data

In order to obtain reliable vehicle speed data, we performed a camera-based measurement on an urban straight road in Duisburg, Germany with a speed limit of 50 km/h. The decision for this road was made because there is no influence on passing vehicles e.g. through traffic lights, speed cameras or obstructed view. Consequently, all road users can choose an appropriate personal speed taking into account the speed limit.

During the evaluation, only vehicle speeds in flowing traffic were taken into account. The related empirical speed histogram is shown in figure 3 (light blue boxes). The single vehicle speeds are distributed widely, which stays in contrast to the former assumption v_{free} = *const.* It seems like the histogram has an asymmetric shape. Due to the relatively small dataset of 432 vehicles, this could also have been a coincidence. That is why we chose a normal distribution to fit the underlying data. With regard to a simple solution on the one hand and taking into account the basic characteristics of the dataset on the other hand, the distribution adapts satisfactorily.

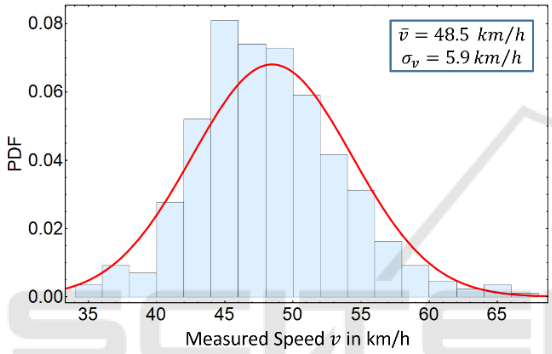

Figure 3: Empirical speed histogram of 432 vehicles in free flow on an urban road in Duisburg, Germany. There is a speed limit of 50 km/h. A normal distribution (red line) satisfactorily fits the data. The underlying parameters for mean $\bar{v}$ and standard deviation σ_v are shown in the upper right corner. The error (±2 km/h) of the measured speed dataset is of the same size as the histogram's bin width.

2.3 Normal Distributed Free Flow Parameter

Motivated through the empirical speed histogram in figure 3, we randomised the value of the free flow parameter v_{free}. It is now following a normal distribution.

As a result, every car is initialised with its own individual free flow speed. Of course, fluctuations are still possible through the underlying stochastic model. Mapping the empirical distribution from subsection 2.2 to a speed limit of 30 km/h, delivers a mean of approx. 29 km/h. However, the standard deviation is expected to remain the same (~6 km/h).

Subsequently, the same procedure as in subsection 2.1 takes place following the rules of the Kerner-Klenov model.

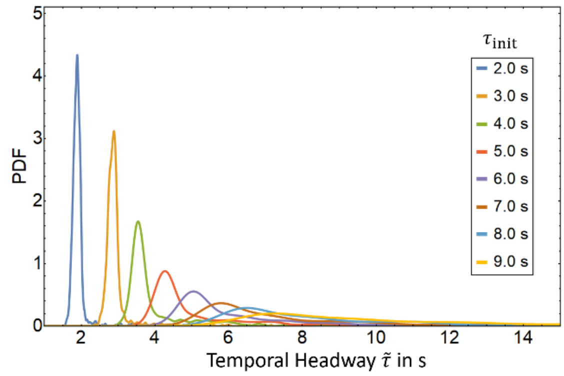

Figure 4: Probability density function (PDF) against the temporal headway $\tilde{\tau}$ at the intersection point x_{int} for different initial temporal headways τ_{init}. For each vehicle, the free flow parameter v_{free} is not constant, but is randomised following a normal distribution. All vehicles are initialised at x_0 (see figure 1). Due to this empirically motivated modification, more softened distributions are resulting, i.e. the statistical temporal headway scatters within a wider range.

However, for this case, we obtain fundamentally different distributions (figure 4) in comparison to the previous case (figure 2). Now, they are much more softened and the peak-like behavior is gone, i.e. the statistical temporal headway $\tilde{\tau}$ scatters within a wider range. With regard to a more quantitative explanation mean, variance and skewness of the distributions are listed in Table 2.

Table 2: Mean, variance and skewness of the distributions shown in figure 4.

τ_{init} [s]	Mean [s]	Variance [s²]	Skewness [s³]
2.0	1.91	0.07	7.26
3.0	2.96	0.29	5.28
4.0	4.04	1.31	3.20
5.0	5.17	2.87	2.54
6.0	6.18	3.64	2.45
7.0	7.28	5.23	2.35
8.0	8.18	5.27	1.33
9.0	9.45	7.88	1.09

3 DISCUSSION

Although the Kerner-Klenov model exhibits stochastic components, the fluctuations for a moderate traffic flow are very slight, obviously. Only when the model is applied to bottleneck situations, the characteristics of real traffic are reproduced realistically and the fluctuations of the model increase. Due to the slight model fluctuations, sharp peaks are resulting (figure 2), i.e. the temporal headway $\tilde{\tau}$ is not changing significantly within the range from x_0 to x_{int}. This behaviour does not seem to be realistic at all. In Table 1 mean, variance and skewness are listed to enable a quantitative point of view.

Compared to other works, where often only averaged empirical data over many cars is shown, our dataset consists of single vehicle information. The measurement took place on a bright day without any precipitation in April 2018 on a straight road in Duisburg, Germany exhibiting a speed limit of 50 km/h. Only vehicle speeds in flowing traffic were taken into account. In order to make sure that the driving behaviour of individual cars was not affected by the measurement, the cameras were placed hidden. Two road markings with a distance of 20 meters in between served as an aid to determine speeds of passing vehicles. Due to the associated averaging process of the vehicle speeds within a range of 20 meters, an error of ±2 km/h should be taken into account. This corresponds to the bin width of the histogram shown in figure 3.

In order to obtain a more realistic behaviour within the framework of a microscopic simulation, a randomised free flow parameter v_{free} was chosen for different initial temporal headways τ_{init} (figure 4). When comparing the different distributions of $\tilde{\tau}$, it is noticeable that they are getting wider (increasing variance) with increasing τ_{init} (table 2). However, the skewness is continuously decreasing. This is due to the safe space gap g_{safe} of the Kerner-Klenov model, which represents the lower limit of the gap between two consecutive vehicles. If the gap is already small, there are many more possibilities for an increase. The bigger it becomes, the more balanced options there are for the underlying agent leading to a more symmetric shape of the related distribution. The mean value of the temporal headway $\tilde{\tau}$ stays very close to the initial value τ_{init}.

It is interesting to see, that the results of subsection 2.1 and subsection 2.3 differ not only in variance, but also in their skewness (compare table 1 to table 2). Whereas a negative skewness is obtained for a constant v_{free}, the skewness becomes positive for a free flow parameter following a normal distribution. A comparision of the mean values shows, that both are systematically smaller than the underlying initial value τ_{init}.

For the following qualitative discussion, we now turn to figure 5 showing a single distribution of $\tilde{\tau}$ from figure 4 (τ_{init} = 6 s). It seems that the mode of the

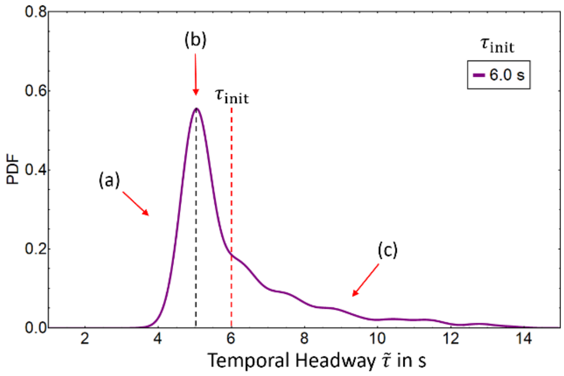

Figure 5: Qualitative discussion on the PDF for v_{free} following a normal distribution. As an example, the distribution for the simulation of τ_{init} = 6 s has been chosen (see figure 4), which is representative of all. Compared to the PDF's heavy tail towards larger temp. headways $\tilde{\tau}$ (c), the distribution has a steep slope towards shorter $\tilde{\tau}$ (a). The mode (b, black dashed line) is systematically smaller than the underlying initial temp. headway τ_{init} (red dashed line).

distribution is systematically smaller than the underlying initial temporal headway τ_{init}, i.e. most of the cars within the analysed ensemble tend to close the gap to their preceding vehicle. The distribution has got a steep slope on its left-hand side. It looks as if there is a lower limit relating to short temporal headways $\tilde{\tau}$ for a given τ_{init}, whereas the heavy tail's range towards larger temporal headways $\tilde{\tau}$ cannot be determined clearly.

4 CONCLUSIONS

We found out that the typical probability density function (PDF) describing the temporal headway development do not have a symmetrical shape. A heavy tail behaviour towards larger temporal headways $\tilde{\tau}$ occurs, if the free flow parameter v_{free} of the underlying Kerner-Klenov model follows a normal distribution. This shape seems to be qualitatively independent of the initial temporal headway τ_{init}. Providing this information to an automated vehicle helps to find the most efficient driving strategy for merging into the ongoing traffic.

We would like to compare our results to real traffic temporal headway distributions. With regard to the described scenario, we are developing a stationary infrared sensor system including multiple units to detect a large number of passing vehicles. Using the generated data helps us to adjust the model's underlying functions and parameters in order to describe real traffic more reliable. Furthermore, this research is going to be shared within the "MEC-

View“-project. The aim is to optimise the algorithm finding the most efficient driving strategy for the involved automated vehicle approaching the project’s T-intersection.

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