Modeling concepts for mixed traffic:
Steps towards a microscopic simulation tool for shared space zones

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ABSTRACT

This paper presents a first step towards a simulation tool for shared space, including all three prevailing individual modes of transport – cars, bicycles and pedestrians. In contrast to conventional roads, behavior cannot be modeled by following a predefined path and strictly obeying traffic rules because the architectural design allows for many more degrees of freedom. Therefore, our research has focused on two main aspects: First, finding a path for each individual and second, handling potential conflicts with other individuals.

The need for a simulation tool arises, as many urban planners see shared space as a modern design concept for busy urban roads. As a result, a growing number of cities are interested in experimenting with shared space zones but are uncertain about safety issues and the effectiveness of the design. While mature simulation tools exist for conventional road designs, no such tool is available for shared space designs, as there are added degrees of freedom in movement as well as more complex social interactions.

To tackle these problems this paper takes the approach to create an infrastructure model which helps all agents to find a path to their destinations. Furthermore, a separate conflict handling system detects when two agents would collide when following their paths. These conflicts are resolved using game theory by maximizing a utility function for different strategies.

First results are presented to give a preliminary assessment of the functionality of the proposed shared space simulation model and its calibration using real trajectories from a existing shared space.
INTRODUCTION

Many urban planners see shared space as an answer to the growing potential for conflicts on busy urban roads resulting from a change in modal split away from a domination of motorized individual transport. In shared space designs, the segregation between motorized and non-motorized traffic is removed, creating an integrated space without traffic signs or signals, curbs and road markings. Instead, traffic flows are controlled by social interactions and supported by intelligent infrastructure measures like colored floors or bollards. Due to this lack of legally binding elements like pedestrian crossings, people are said to be more safety-conscious and to pay more attention to the behavior of other people. Especially the high potential of conflicts between different types of road users is said to be minimized. In conventional designs the separation of traffic flows by modes was used to avoid these conflicts between cars, buses, pedestrians and bikes. However, proponents of the shared space approach claim that this is an outdated concept leading to unintended consequences (1, 2):

- Attention of traffic participants in one mode towards those in different modes is lessened as they feel safe and privileged on “their” assigned part of the road.
- As a consequence cars, but also bikes and other motorized traffic exceed the speed limits and concentrate mainly on “their” part of the road leading to a higher risk for pedestrians.
- While modal splits are changing away from motorized individual traffic (MIT) current street designs are not flexible enough to adapt to unexpected shifts and tend to prioritize MIT hindering the development of “green” transportation.

There is ongoing debate about the merits and practicality of shared space ((2), (3)). However, across Europe, in particular Holland, Germany and the UK, several shared space projects have been planned and established. Furthermore, some practical analyses on existing shared space schemes show the effects of shared space. Topp (5) concludes that safety related data in before and after analysis show a neutral tendency in accident statistics of self organizing shared space areas. Trial demonstrations at three junctions in Bristol (UK) showed that they generally performed better after traffic signals had been voluntarily turned off (4). However, these shared space analyses are carried out as experiments or before and after studies but do not help traffic planners to judge concrete projects in advance with respect to safety and traffic flow. Good planning tools are necessary to help convince the public as well as local authorities that well designed shared space areas are advantageous for travelers in all modes (2), (3).

Problem Statement

The most essential phenomenon when modeling mixed traffic areas is the social behavior within the interactions between cars, pedestrians and bicycles. This can be observed in situations where pedestrians want to cross a road without a crosswalk and cars (sometimes) stop without the normative need to stop only due to social factors. In slightly different situations, the same pedestrian would make a small direction change to walk behind the car instead of waiting for the car to pass. Modeling this and similar behavior is one of the main challenges when designing shared space simulations. This paper shows the first steps towards such a model.

To the authors’ knowledge no available simulation model can explicitly handle the requirements that the added social interactions and constraints imply, yet. Such constraints include:

- Finding the way through the infrastructure is more complex because there is no hard separation between different traffic modes. Desired speeds are strongly dependent on the traffic situation and not only on speed limit and vehicle platooning constraints.
Interaction between different types of road users including pedestrians, bicycles, and cars need to be handled differently from conventional roads. Instead of modeling technical regulations like traffic lights, there is a need to model the social interactions between people in different transport modes.

**Related Work**

Up to now, research of shared space concepts has mostly focused on empirical studies showing the impact of shared space, instead of creating simulation models. It is hard to imply a simulation model from these works as the causalities of a measure to an effect is not always clear. Individual aspects were analyzed by Richter and Zierke who show that removing the separation between lanes on a country road effectively reduced speeds of cars (5), Davis in turn shows that reducing speeds of cars increases safety of pedestrians (6).

While there is no combined simulation tool for shared space many approaches to microscopic simulation of a single mode exist in the scientific literature. These are useful starting points for a shared space simulation model. Two commonly used model classes used for microscopic simulation are Cellular Automata (CA) (pedestrians (7), cars (8)) and physic analogies like social force models (pedestrian (9), cars (10)). These models provide a good foundation for handling basic interactions between agents from the same mode. Therefore the work in this paper is based in large parts on the model suggested in (9).

Less research has been performed on the interaction between individuals using different modes. Most current publications dealing with conflicts between pedestrians and cars concentrate on a rule based approach, where the right of way is given by the infrastructure, e.g. a pedestrian crosswalk (11) where cars give way to pedestrians within a certain area close to the crosswalk. Kaparias et al. is one of the few references which explicitly researches social interaction by fitting a discrete choice model on the willingness of drivers to share space with pedestrians according to different input factors (12). Other examples of interactions between different modes include the merging behavior of cars and motorcycles that relies on the fact that motorcycles can fill the spaces left by cars. Lan and Chang (13) demonstrate a CA with the capability to model heterogeneous traffic of cars and motorcycles. The aspect of heterogeneity is considered by using different number of cells and stochastic CA rule sets. Lee (14) discusses the model constraints in interaction and lateral behavior. He concludes that the CA algorithms and rules are convincingly effective but might not be capable to produce realistic tactical maneuvers.

**Outline of the paper**

Following the approach presented in (15), all agents in the simulation (cars, bikes and pedestrians) are modeled individually using microscopic models. The presented simulation framework is divided in three layers of models which build upon each other:

1. First we introduce our **infrastructure model** which is used to find an individual path for each agent according to its origin-destination pair.

2. The next core element is the **operational model** – a social force (SF) model adapted for the use in all transportation modes. Therefore, we add vehicle dynamics to produce mechanically feasible vehicle trajectories from the social force results.

3. Finally, we add a separate **tactical model** using a game theoretic approach for handling road conflicts that cannot be resolved by following the social force paradigm alone.

In the last section, we use data collected in an existing shared space design to do calibration and feasibility tests of the game theoretic model.
INFRASTRUCTURE MODEL

In this section we describe how the infrastructure of a shared space object influences the simulation model. Every person who walks or drives through these shared spaces is assumed to have a goal. Finding the path to the goal is strongly influenced by the structure of these self-organizing roads. Obstacles, colored areas and other infrastructural elements heavily influence the road user’s path to their goal.

Therefore, as Schönauer and Schrom-Feiertag have proposed in (15), the infrastructure is described by forces keeping the agents on their track, avoiding obstacles and using their individual preferences. This hypothesis is then extended to an individual interpretation of the lateral position, leading to a lateral distribution. The attractiveness potential field \( U_g \) provides a rasterized numeric field on the road plane, representing preferred lateral positioning on the chosen path in the network. In the next step, \( U_{ag}(r_{ag}) \) gives the potential for the specific agent \( \alpha \) on the associated guiding field \( g \). The relative position vector \( r_{ag} \) describes the shortest distance from the agent to the guiding field. Finally (1) shows the created force vector \( f_{ag}(r_{ag}) \) which “pulls” the agent to the lateral maximum of the attractiveness potential field.

\[
f_{ag}(r_{ag}) = \nabla_{r_{ag}} U_{ag}(r_{ag})
\]  

(1)

For calculation of this field, we divide the simulation space into multiple areas: Straight sections and intersection areas. Handling intersections is harder, due to a higher diversity of road design and a multitude of possible routes. Figure 1 shows an overview and visualization of obtaining the guiding field for a car making a right turn.

![Image](a) Original scene. ![Image](b) Sections in the model. ![Image](c) Guiding field’s maxima. ![Image](d) Force vector field.

FIGURE 1 Obtaining the guiding field for the silver car. The original topology (a) is segmented into sections (b), (c) shows both guiding field’s maxima for a car turning right or of heading straight (for visualization purposes only). (d) shows the vector field with forces keeping the silver car on its track when turning right (guiding field from (c) transferred to world coordinates).
Guiding fields for pedestrians and bicyclists are obtained similarly. Even without explicit sidewalks, people have to walk on the side of the road. Bicyclists are allowed to use the same path as pedestrians, while some might use the center of the road – just like cars. Thus, the individual guiding field for bicycles is determined by the desired velocity of the agent. For guiding field calculation in intersections, the same algorithm as for cars is used.

While basic assumptions are made where different road users usually drive or walk, it is important to note that this field is not manually created but modeled. The calibration of this guiding filed model using real world data is future work.

### OPERATIONAL MODEL

While the infrastructure model can provide a likely path for agents in free flow, we also need an operational model which can handle pedestrian and vehicle dynamics when following this path. Furthermore, such a model can handle basic social interactions like making small directional changes to avoid hitting each other. For modeling operational behavior we use the multi-agent social force model (9). This works well for pedestrians and by extending it with a vehicle dynamic model we can respect the limited degrees of freedom of cars and bicycles. This approach allows the operational modeling of interactions among road users and between a road user and the infrastructure.

#### Social Force Model

Social force models are using analogies to Newtonian mechanics, where infrastructure and agents emit individual force fields. An agent's acceleration is modeled as a function of the inbound force vector in the simulation environment.

The energy to let the agent $\alpha$ accelerate towards their goal is introduced by the driving force $\bar{f}_{\alpha}^0(t) = \frac{\nu_0^0 \cdot e_0^\alpha(t) - \bar{v}_\alpha(t)}{\tau_\alpha}$ which motivates the agent to maneuver to a target in the road network with a desired velocity $\nu_0^0$ in direction of $e_0^\alpha(t)$ towards the goal depending on the current velocity $\bar{v}_\alpha(t)$ and controlled by the parameter $\tau_\alpha$ called relaxation time. The force accelerating the agent to the goal and away from obstacles is given by

$$
\bar{f}_{\alpha SF}(t) = \bar{f}_{\alpha}^0(t) + \sum_{\beta \neq \alpha} \bar{f}_{\alpha \beta}(t) + \sum_i \bar{f}_{\alpha i}(t),
$$

where $\bar{f}_{\alpha \beta}(t)$ is the force accelerating $\alpha$ away from agent $\beta$ and $\bar{f}_{\alpha i}(t)$ is the force accelerating the agent away from the infrastructure.

This approach was first discussed by Helbing and Molnar (9) in a traffic engineering context. As described above we add the force $\bar{f}_{\alpha g}(t)$ to enable the inclusion of the guiding field. This leads to the formulation

$$
\bar{f}_{\alpha}(t) = \bar{f}_{\alpha g}(t) + \bar{f}_{\alpha SF}(t)
$$

In pedestrian simulations the dynamic and kinematic considerations in the control model between the psychological to the physical human part are widely reduced to a delay time $\tau_\alpha$. For vehicles the controllable degrees of freedom are less than the total degrees of freedom. These nonholonomic properties constrain the ability to move the vehicle directly to the desired direction.

#### Vehicle Dynamics

These constraints must be added by a separate vehicle control model which respects the dynamic of cars. A lot of research has been done in the area of vehicle dynamics and many models with...
different computational complexity and accuracy exist. For this paper, we have decided to use the
discrete form of single track model for modeling cars dynamics using the equations from Kramer
as shown in (16). The single track model is a widely used vehicle model for lateral control issues.
The wheel gauge of the rear and front tire pair is not considered, the axles are reduced to a single
track along the longitudinal center line of the vehicle. For dynamic equations, figures and
parameters of the applied model the interested reader is referred to Huang et al. (17).

Since the vehicles will be guided by social and infrastructural forces a control system has
to stabilize the driving on an appropriate path during the simulation. On the one hand the lateral
component of the force is the main input of the steering model, while on the other hand the
longitudinal part of the force controls acceleration and breaking of the vehicle model. The input
forces are given by social interaction with other agents, by obstacles, the target vector plus the
guiding field of the infrastructure.

In the simulation the error measurements obtain the error by applying the vehicle model
continuing at the current steering angle ($\delta = 0$) for a time period $T_p$. Figure 2 illustrates the
preview (gray object) during the simulation and the generation of the error vector. $\delta$ represents
the steering angle, $\beta$ is the slip angle, $d\psi$ is the yaw rate while the relevant control input is $\overline{f_{\alpha SF}}$
and $\overline{f_{\alpha g} (t)}$ and the preview distance $D_p$.

FIGURE 2 Obtaining the preview angle error of the guiding force and the social force. The vehicle's grey
replication is the projection in the next time step. The accumulated error angle $\varepsilon_\beta$ is the input variable in the
driver-vehicle controller unit. $W_i$ represents the weighing function, quantifying the errors at different preview
times.

The preview distance is essential for stabilization of the vehicle. In this paper a constant preview
time is used for the lateral control inducing a preview distance $D_p [m]$ linearly growing with
speed.

Application on a simulation of turning cars
In this section the application of the previously described models for a turn is presented. Within
the network of a redesigned through road in Gleinstätten (Austria), car turnings at an intersection
are simulated and the lateral track choice and the speed profile are verified with real trajectories.
Data has been obtained by manually annotating video footage which was taken two months after the spot has been opened after reconstruction. Figure 3 shows a rendered trajectory of a single car in the video footage for the example of a right turning. The parameters used in the control and the vehicle dynamics are given in (17).

Figure 3 (a) Real driving trajectories of turning vehicles in the Shared Space scheme are obtained. (b) Real and simulated trajectories of passenger cars ($n_{\text{data}} = 15$, $n_{\text{sim}} = 50$). The blue line represents the mechanical or optical separation from the side areas.

In Figure 3b a spatial overlay of simulated (red) and real world trajectories is presented.

As the reduction in speed is triggered much earlier than the steering impulse, the speed control uses the tactical preview time $T_T > 2$ seconds. The preview time $T_T$ leads to the tactical preview distance $D_T = \int_0^{T_T} v(t)\,dt$. The preview distance $D_T$ determines both the deceleration and the acceleration point. The same $D_T$ will be applied in identifying conflicts (next chapter).

Figure 4 shows the deceleration and acceleration process in the right-turn. The curvature line indicates the road orientation. The sample size is 15 for real world data.

**FIGURE 4** Speed profile of cars turning 90°. From the graph it becomes apparent that the real drivers use a higher preview distance than the cars in the simulation.
The speed profile of the real data shows another phenomenon in lowering speeds in the observed path at 250m: A bottleneck in the road design causes deceleration to a lower speed level, while the curvature detector doesn’t strongly react to this road feature. It has to be considered that the full calibration of the social force parameters is future work.

**TACTICAL MODEL**

Social interaction is the precondition of mixed traffic at giving way processes, road crossing and lateral evasion. At low speeds (which are typical for pedestrians) the social force model ensures good fitting with empirical data even in high traffic densities. Including vehicular traffic in the simulation, however, higher foresights would be needed but those exceed the capabilities of social force models. Furthermore, voluntary actions like making a stopping to let a pedestrian pass are much more common in shared spaces and therefore need to be addressed separately.

In this study therefore, we add decisions made by a tactical conflict solving system as an additional force $f_{tactics}(t)$ to the existing forces. Hence, the resulting force vector $\vec{f}_e(t)$ of each agent is the sum of the forces of the infrastructure guiding field $\vec{f}_{ag}(t)$, of the adapted social force model force $\vec{f}_{tSF}(t)$ and the new tactical force $\vec{f}_{tactics}(t)$

$$\vec{f}_e(t) = \vec{f}_{ag}(t) + \vec{f}_{tSF}(t) + \vec{f}_{tactics}(t) \quad (4)$$

The next sections describe this tactical conflict solving system. First we need to explicitly detect situations where a possible conflict between agents occurs which cannot be handled by the standard operational model. Each conflict has potential strategies to be solved like stopping or dodging to the side. A Stackelberg game is run to decide which strategy has the highest pay off.

**Conflict Detection**

Conflict detection is done in regular intervals (one second seems to be a reasonable tradeoff between detection in time and processing effort). Each agent is simulated on its own without taking any other agents into account. The resulting trajectories indicate the exact path which would be taken if no other agents were involved in the scene. All these trajectories are then compared to find pairs conflicting in time and space. Within a certain radius around agents other agents are considered to be relevant for interaction.

Once a conflict has been found, the conflict is parameterized with both agents’ state vectors, path and the normative situation. The angular classification is the first estimation before further processing. Three types of conflicts are distinguished: **PERPENDICULAR**, **HEAD ON** and **REAR**. For each class a method to fill the game matrix is created.

**Conflict Handling**

Interaction processes on the tactical level are modeled based on game theory. Game theory has previously been applied on road traffic interaction in urban contexts by Li and Chen in (18), where gap acceptance behavior on highways was modeled. Also Kita ((19) formulated a game for car conflicts. We extend this game for handling multi-modal conflicts. To describe this situation as a game, we must specify the type of game, the number of players, the number of games repeated, and whether the game allows cooperation. For simplification reasons we reduce the number of active players in a single game to two. However, the conflict handling of a pair of agents $i,j$ also influences other traffic participants surrounding them. This influence comes back to both original partners via the reaction of the surrounding agents, consequently all the agents in the vicinity of the conflicting partners can be recognized as interacting players.
Repetition of the game has to be defined. For our purposes, we assume that the number of games is one for each of the agent pairs in conflict, and the games are independent from one another. This is because the amount of time that the agent has to make a decision is not so long that he or she can make multiple decisions, and because each decision is not affected by preceding or following decisions, but is rather taken independently.

The possibility of receiving information about the other agent leads to the potential of cooperation. Both players can observe the other agent's situation and have full information about the strategies of the other one, i.e. the pay-off matrices. The agents, however, have no way to exchange their decisions about executing the strategies. The game is therefore characterized as a non-cooperative game with perfect information.

Due to simplification issues the possible strategies for conflict solving are reduced five. Figure 5 drafts the spatial conflict situation and its strategy alternatives.

**FIGURE 5** Without reacting, the two agents would collide shortly afterwards in point $s_{i1}$ respectively $s_{j1}$. When the conflict is identified, agent i is located at $s_{i0}$ and agent j at $s_{j0}$. In a spatial context the 5 strategies of agent i are given by $s_{i1}$ to $s_{i5}$. The alternatives of agent j are not shown in order to keep the overview as simple as possible.

Besides the zero strategy $s_{i1}$/$s_{j1}$, the strategies of decelerating, accelerating and dodging left or right are considered. The pay-off values are given by exogenous variables which are speed, type of agent, time to the theoretical collision, the ideal path and the traffic regulations.

**Game Solving**

The presented conflict solving approach is based on a rational game play. This means, for the same input variables, the game has a deterministic outcome. A Stackelberg game is a non-symmetric hierarchical game with leader and follower players – originally introduced to model unbalanced markets (20). The leader who holds the powerful position announces its strategy, and followers react to the leader's announced strategy. Due to the perfect information the leader knows the follower’s answer ex-ante to its own strategy. Simplified illustration in road traffic crossing conflict: The car driver knows the pedestrian is most likely going to stop if the car driver continues with full speed. In the proposed model normative and social aspects can shift the leader's optimum towards stopping.

Solving the Stackelberg model is done by finding the subgame perfect Nash equilibrium (SPNE), after calculating the best response functions of the follower. The SPNE can be deduced
by backward induction. We denote the sets of options the two players can choose from as $S_i$ for
the leader and $S_f$ for the follower. Let $u_i(s_i, s_f)$ be the utility of the leader when the option
$s_i \in S_i$ is chosen and the follower reacts by the move $s_f \in S_f$ and similarly $u_f(s'_f \mid s_i)$ the utility
of the follower dependent on the choice of the leader. Let $\beta_j(s)$ be the set of best answers to $S_j$.

$$\beta_j(s) \equiv \{s'_j \in S_j \mid u_j(s'_j \mid s_i) = \max_k u_j(s_k \mid s_i)\}. \quad (5)$$

Then the SPNE $S^\text{eq}_i$ is stable for both players, providing that player $i$ chooses the maximum of
the utilities dependent on the choice set $\beta_j(s)$ of the follower $j$:

$$S^\text{eq}_i = \max_{s_i \in S_i} (u_i(s_i, \beta_j(s))) \quad (6)$$

### Payoff estimation

Multiple components are considered to estimate the utilities of both agents for every strategy pair $S_{ij}$. The reduction of the conflict level gives the same pay off for both agents. Normative and
social behavior and discomfort and travel time factors are calculated separately. The utility of a
decision pair $(s_i, s_f)$ is given as a weighted sum of all partial payoffs for both players:

$$u_i(s_i, s_f) = \sum_{c=0}^{n} \theta_c \cdot U_{ct} = \sum_{c=0}^{n} \theta_c U_{ct} \cdot u_f(s_f \mid s_i) = \sum_{c=0}^{n} \theta_c \cdot U_{cf} \quad (7)$$

$U_{ct}$ represents the utility matrices for every utility component including: $U_{ct}$ is the entry
$(l, f)$ from one of the utility component matrices corresponding to that decision. For our game
we use the following utilities (note that utility matrices that agree for both players are denoted by
a subscript $ij$ while otherwise they are denoted with a single subscript):

1. $V_{ij}$, collision avoidance $u_{v_{ij}}$, collision probability disutility coming from speed
differences, utility calculated as $-\exp (\theta_v (v_{rel} - \max_{nm} (v_{nm}^{rel})))$, where $v_{ij}^{rel}$ is the relative speed
after following the strategy pair $S_{ij}$

2. $R_{ij}$, collision avoidance $u_{r_{ij}}$, length of the spatial relative vector of collision
probability disutility coming from distance, utility calculated as $-\exp (-\theta_r r_{ij})$, where $r_{ij}$ is the
distance between the agents after following the strategy pair $S_{ij}$

3. $T_{ij}$, collision avoidance $u_{t_{ij}}$, collision probability disutility coming from time distance
tij at the intersection of the projected trajectories of $S_{ij}$ calculated as $-\exp (-\theta_t t_{ij})$.

4. $SU_{ij}, SU_{ij}$ social utility for agents $i, j$ given as $SU_{ij}(i, j) = 1$ when the decision $(i, j)$ is
supported by social convention and 0 otherwise, i.e. for a car it is socially preferable to let the
pedestrian cross the street.

5. $D_{ij}^l, D_{ij}^l$, saved detour utility, given as $\exp (-\theta_{tl} (d_{tl}^l - \min_k (d_{kl}^l)))$ where $d_{tl}^l$ is the
distance of the leader after three seconds of alternative $i$ to their goal (respectively for the
follower)

6. $E_{ij}^l, E_{ij}^l$, energy loss disutility utility (zero-strategy = 0) of the agents $i$, given as the
negative absolute value of the velocity change.

7. $N_{ij}^l, N_{ij}^l$, normative utility according to traffic regulations (give way etc.) for agents at
decision $S_{ij}$
Note that the utilities (except for the energy loss) are in the interval $[0, 1]$ and $[-1, 0]$ for disutilities.

The utility weight set $\theta = (\theta_v, \theta_r, \theta_t, \theta_d, \theta_s, \theta_n, \theta_v, \theta_r, \theta_t, \theta_d, \theta_f)^T$ are calibration parameters. This requires the full data of the exogenous variables and an interpretation of the decisions in the conflict solving process.

**Application on pedestrians crossing the road**

In this paper the tactical model is applied to interactions of pedestrians and cars within a shared space designed road. A total number of 60 trajectories of interacting scenes have been extracted from video footage resulting in 15 conflict descriptions. Figure 6 shows one of these interacting scenes, where a pedestrian wants to cross the road while a car is approaching.

![Figure 6](image)

(a) Conflict detection

(b) Conflict handling strategies

**FIGURE 6** (a) A conflict is detected whenever two agents want to occupy the same space within a similar time interval in the near future. Solid lines indicate past trajectory data of the agents, dotted lines simulated future positions. The circles indicate the projected position at the same time. (b) Each agent can choose from different strategies: The pedestrian can continue, walk left or right or stop; the car’s possibilities are limited to continue and stop in this game. In this particular example the car stops and the pedestrian continues.

In this particular example the car stops and the pedestrian continues, other input variables like different time to collision might yield different results. For our analysis we assumed the pedestrian to be the leader in the game. Furthermore, we restricted the behavior of the car to stopping or continuing as the possibilities to turn were restricted by oncoming traffic on one side and the edge of street markers on the other (see Figure 5). Furthermore accelerating was not assumed to be a viable option as it does not seem a socially acceptable alternative.

The estimation of the weights is done by fitting the game results to the observed conflict solving outcomes by estimating $\theta$. Since the decisions of the game are done using a utility maximization approach, for identifiability reasons one parameter is set to 1 as only differences in utility influence the decision. We choose the parameter $\theta_n = 1$. The parameters were estimated in Matlab using the genetic algorithm (GA) function.

An example of the calculated utilities can be seen in **TABLE 1** for a scenario where the pedestrian continued in the original speed, while the car slowed down to let the pedestrian pass.
TABLE 1 Disutilities of pedestrian (LEFT) and car (RIGHT) using the fitted parameter set. The choice set for the pedestrian with respect to the disutilities for the car is given in the gray cells. The final choice of the leader is given in red and corresponds to the observed choice in the data.

<table>
<thead>
<tr>
<th>Ped. Car</th>
<th>Cont.</th>
<th>Brake</th>
<th>Left</th>
<th>Right</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continue</td>
<td>-3.06</td>
<td>-1.18</td>
<td>-1.82</td>
<td>-1.35</td>
</tr>
<tr>
<td>Brake</td>
<td>-0.99</td>
<td>-0.58</td>
<td>-1.05</td>
<td>-1.16</td>
</tr>
</tbody>
</table>

Due to the small amount of viable decisions collected we decided not to present the estimated parameters here, as there is doubt if such a procedure can represent a parameter set usable in a general setting. Instead we just did a sensitivity analysis of the collected parameter sets. For the sensitivity analysis, we changed the fitted parameters one by one. We chose a range from -95% to +95% of the original parameter values. The result can be seen in Figure 7.

FIGURE 7 Sensitivity analysis of the decision power of the \( \theta \) parameter. 100% represent the maximum number of the correct classifications in the current model.

One can see that all parameters show some sensitivity to changes and we conclude that the variables are chosen such that they all influence the decisions of the players. While there is little sensitivity to an increase of the first 4 parameters, this might not be problematic as the addition of more complex scenarios should improve the quality of the parameter estimates.

CONCLUSIONS AND OUTLOOK

In this paper we have adopted the social force model for cars by using a dedicated vehicle model with an additional linear controller keeping the vehicles on a preferred path. This path is represented by an infrastructural guiding field and is fed into the controller together with social forces and forces from the vehicle model. First results from comparing the observed trajectories with the simulated ones showed that this approach can model cars in a shared space infrastructure...
quite well. More research is needed for properly predicting paths for bicycles and pedestrians because the examined location was mainly dominated by motorized traffic.

While using a social force approach to model interactions between vehicles as well as pedestrians solves many conflicts in a shared space simulation there is need to add a tactical component to allow social interactions like stopping to let someone else go first, contrary to usual behavior in conventional road designs. For this purpose a game theoretic force component was added to the social force model. While we use a non-cooperative game to decide on the force component we can still use this to model cooperative behavior. This is done by adding a social norm component to the utility. Indeed, the parameter significance analysis shows that the social component does have an influence on the game’s outcome and is therefore a relevant part of the model.

In conclusion, the modeling concept of adding several parts, including a socially influenced tactical model into the traffic model shows promise in producing a simulation model for a shared space context. There are several missing modeling steps, e.g. bicycles show different dynamic behavior than cars and hence a dedicated cycle model is required to represent two-wheeled vehicles. The calibration of the models should be expanded to include richer and hence more relevant data-set collected in different shared space environments. Therefore, additional videos from a new shared space in Graz (Austria) were recorded. This shared space design is not only much more complex but also has a much higher frequency of social interactions because the modal share in this area is roughly equivalent between cars, bicycles and pedestrians. Using this data, it is expected, that the models and the calibration will be improved. This should allow the model to be used on a wider range of different mixed traffic concepts.

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