Simulation of individual injury risks with an agent-based transport model

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Introduction

Road safety is one of the critical aspects of transportation in terms of impact on public health. In Germany, 12% of the accident-related deaths are due to traffic crashes, and this number is even higher for the early and middle age group (age from 15 to 35) (*1*). Although there is abundant literature on Crash Prediction Models (CPM) and aggregated analysis of traffic safety (*2–15*), very few studies focused on modeling the injury risk based on individual trips. Moreover, the effect of the characteristics of travelers (such as their place of residence and/or their travel behavior) is generally disregarded in traditional safety studies and analyses are usually rely on aggregated traffic exposure variables, such as the Average Annual Daily Traffic (AADT). As a result, the majority of previous works have to be carried only on a subset of roads, rather than the entire road network due to lack of comprehensive traffic volume data. To overcome these issues, we developed a model that integrates CPMs with an agent-based transport model (MATSim) (*16*) to assess the crash injury risk based on individual trips. The model in MATSim provides the individual paths of a set of agents, defined agent by agent. These can be treated as traffic volumes (aggregated) but also as individual trips (disaggregated). The integrated model is applied in the Munich Metropolitan area to demonstrate its capabilities, using the already generated agent-based multimodal travel demand (*17*)

Methodology

Firstly, we specify CPMs that predict the average number of crashes for different road users including car occupants, cyclists, and pedestrians, using the modeled traffic volume data combined with some roadway characteristics. At this point, the transport demand data is used as an aggregated variable (in users per day) The number of KSI (killed or seriously injured) crashes and the number of light injury crashes is estimated separately for each link.

The incorporation of CPMs and MATSim is not straightforward. The outcomes of CPMs (equation 1) are the average number of accidents occurring on each road segment l over a certain period (e.g. a year) $Crash_l$. CPMs can be estimated by each transport mode independently (car, bicycle and pedestrian).

$$Crash_l = f(Volume_l, x_{geometry}, x_{environment} \dots) \quad (1)$$

where $Crash_l$ is the number of crashes per year in the link l, $Volume_l$ is the average daily traffic volume of link l, $x_{geometry,l}$ and $x_{environment,l}$ are other variables that describe the geometry or the environment at link l. We cannot use it directly to measure the injury risk of each road user. In this study, injury risk R_i is defined as the probability of being injured of a certain agent i over a typical traveling day. Further steps are needed here to calculate the agent injury risk R_i.

First, the average number of accidents $Crash_l$ is disaggregated to the average number of accidents over a certain time of day period $Crash_{l,h}$. With the benefit from agent-based simulation, MATSim provides information on the exact time at which each agent passes through a specified link. This makes it possible to capture different levels of risks varying with time of day. The annual crash frequency is converted into a daily average crash frequency. Then the number of accidents on link l at time h is calculated by multiply the daily average crash frequency by the weight of time h, as seen in equation 2. The weights here are generated from the crash distribution over time of day based on the German accident data from 2016 to 2018.

$$Crash_{l,h} = \frac{Crash_l}{365} * Weight_h \tag{2}$$

The consequence of an accident can be more than one casualty, involving different road users and varying in severity. To measure the risk of being injured or killed per road user passing through the link, the estimated number of accidents needs to be converted into the number of casualties for different travel modes m by severity levels s, as defined in equation 3.

$$Casualty_{l,h,s,m} = Crash_{l,h} * Casualty\ Ratio_{s,m} \tag{3}$$

where m is the travel mode including car occupant, cyclist, and pedestrian; s is the casualty severity including light injury and KSI. Casualty ratio refers to the average number of person got injured/killed in an accident. The casualty information is not provided in the German accident open dataset. Therefore, we draw these ratios on the accident and casualty records from the UK STATS19 police database.

Subsequently, the injury risk of link l at time h is calculated by dividing the number of casualties $Casualty_{l,h,s,m}$ by the measure of exposure, as expressed in equation 4. The exposure is calculated as the product of the traffic volumes and the length of the road, generally expressed as person-kilometer traveled. Traffic volumes of private cars, cyclists, and pedestrians are extracted from MATSim.

$$R_{l,h,s,m} = \frac{Casualty_{l,h,s,m}}{Exposure_{l,h,m}} = \frac{Casualty_{l,h,s,m}}{Volume_{l,h,m} * Length_l} \tag{4}$$

Injury risks $R_{l,h,s,m}$ are calculated for all links on the network. The specified links where each agent traveled is simulated in the agent-based transport model. Hence, the injury risk/likelihood of each road user R_i can be calculated by cumulating the risk of all traveled links, as defined in equation 5. $P_{l,h}$ is a dummy variable for whether agent i traveled on link l during time h.

$$R_i = \sum_{l=1}^{links} \sum_{h=0}^{24} R_{l,h,s,m} * P_{l,h} \tag{5}$$

Results

The integrated model is applied to the Munich Metropolitan area to demonstrate its ability to assess the injury risks of each road user. A total of 8 million trips are simulated across all trip purposes. Figure 1 shows the distribution of killed or injury risk of all simulated trips. Risk is normalized by trip distances (kilometer) for comparison among transport modes. In general, car-occupants have the lowest risk of getting killed or injured while pedestrians and cyclists are more vulnerable to exposure to injured risk, which is logical, as it is measured in risk by distance. Pedestrians are always considered as the most vulnerable road user. Figure 1 gives us an indication that cyclists have a higher risk of being slightly injured while pedestrians are more dangerous to being killed or severely injured.

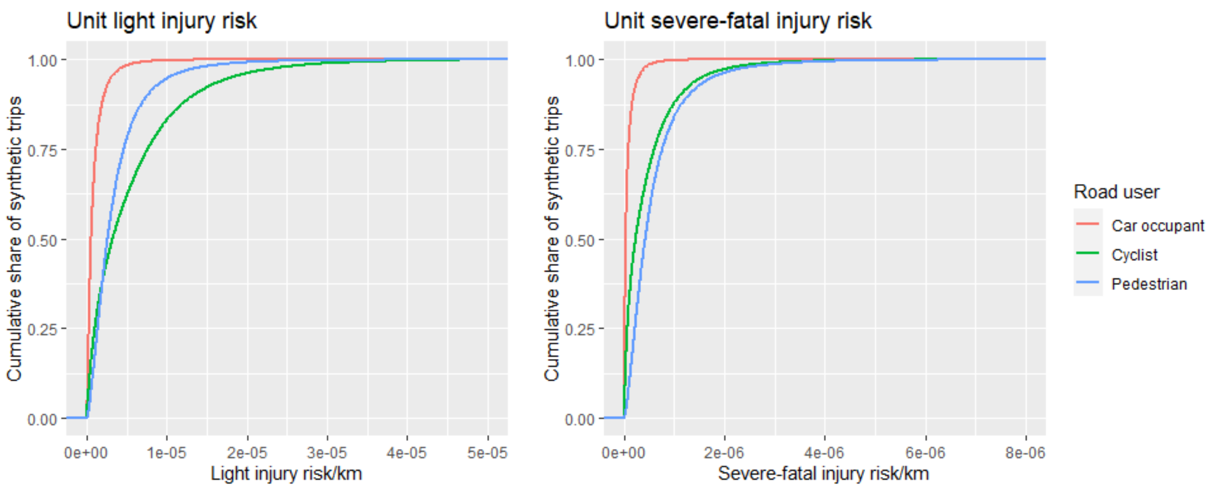

Figure 1 Distribution of modeled Light injury and KSI risk per kilometer of each synthetic trips by transport mode

With the benefits of the agent-based transport model, the home location of each agent is known. This helps us to explore the equity in road safety in terms of where the agents live. Figure 2 (left) shows the distribution of the KSI risk of all simulated agents. It tells us that people living in rural areas experience a higher risk of being killed or severely injured than those living in urban areas. Marshall and Ferenchak (*18*) found the same evidence in the US. Since people living in rural areas might need to travel more kilometers for commuting or other daily activities, the higher risk might result from the higher vehicle kilometers traveled.

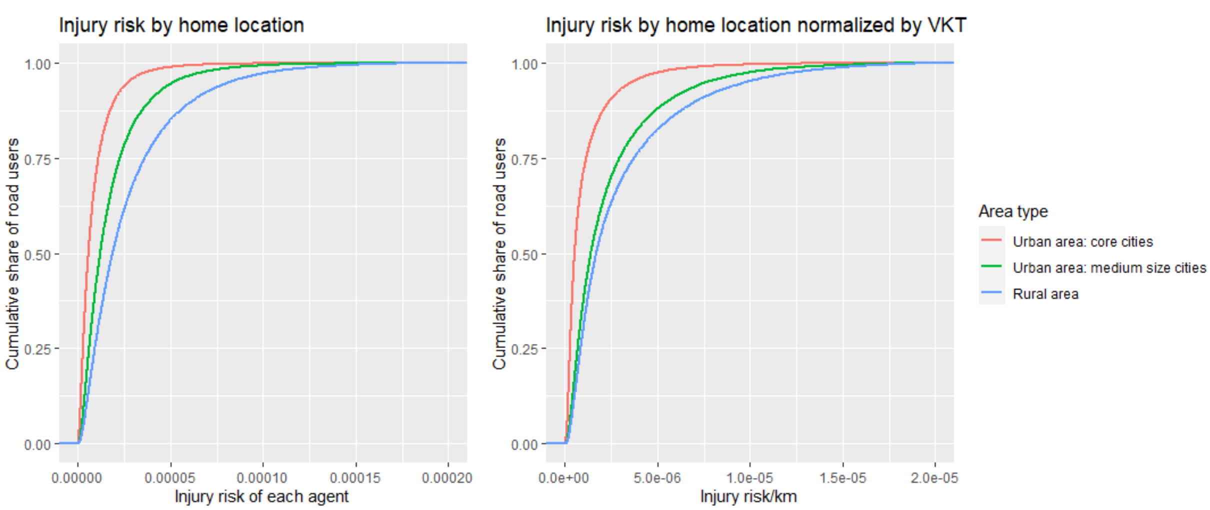

Figure 2 Distribution of KSI risk of each agent (left) and distribution of KSI per kilometer (right) by the area type of home location

Conclusion

Traditional road safety studies are capable of finding out where the crash occurs, and which road facility or neighborhood is riskier. That allows very detailed crash prediction models, that include usually many relevant factors that influence the risk at the analyzed infrastructure. However, such traditional crash prediction models cannot be scaled for large-scale analyses that include every road and every crash. The proposed model analyzes risk at a large scale, thus every road, every trip and every crash can be considered. The method is depending strongly on the fidelity of the transport model, since the errors of the transport model might be propagated to the errors in the location of risk. Despite this limitation, the proposed model allows us to consider road safety from a transport planning perspective. At the same time, thanks to the microscopic nature of the used transport model, we are able to explore the individual risks of using the roads, to understand, for instance, who is exposed to higher risks or the purposes of the trips that are more dangerous. Last, and more importantly, thanks to the use of transport models instead of traffic observations, it is possible to make forecasts into the future, considering potential changes of mode choice decisions or of distance travelled by users.

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