A Non-Signalized Junction Model for Agent-Based Simulations of Car–Pedestrian Mode Mass Evacuations

Maddegedara Lalith 1,*,†, Wasuwat Petprakob 2,†, Muneo Hori 3,†, Tsuyoshi Ichimura 1,† and Kohei Fujita 1,†

1 Earthquake Research Institute, The University of Tokyo, Bunkyo-ku, Tokyo 113-0032, Japan; ichimura@eri.u-tokyo.ac.jp (T.I.); fujita@eri.u-tokyo.ac.jp (K.F.)
2 MAQE Bangkok Co., Ltd., Lumphini, Pathumwan, Bangkok 10330, Thailand; wasuwat.p@hotmail.com
3 Research Institute for Value-Added-Information Generation, Japan Agency for Marine-Earth Science and Technology, Yokohama 236-0001, Japan; horimune@jamstec.go.jp
* Correspondence: lalith@eri.u-tokyo.ac.jp
† These authors contributed equally to this work.

Abstract: During major disasters, such as a subduction earthquake and the associated tsunami, combinations of uncommon conditions such as non-functioning traffic signals, a large number of pedestrians on traffic lanes, and debris scattered on roads can be widespread. It is vital to take these uncommon conditions into account since they can significantly influence the evacuation progress. Agent-Based Models (ABMs) with capabilities to reproduce evacuees’ behaviors as emergent phenomena is promising method to simulate combinations of such rare conditions. This paper presents a new model to cover the current research gap in accurately modeling car–car and car–pedestrian interactions at non-signalized junctions. Specifically, the details of accurately approximating car trajectories at junctions and automated construction, approximating free-flow speed of cars along curved trajectories, and accurately calculating the points of collision and time to collision are presented. As a demonstrative application, we simulated a hypothetical evacuation scenario with non-functioning traffic signals in which different numbers of slow evacuees are allowed to use cars. While the ABM is yet to be thoroughly validated, the presented demonstrative scenarios indicates that a considerable number of the needy can be allowed to use cars for evacuation if their routes and evacuation start time window are well planned.

Keywords: mass evacuation simulation; agent-based modeling; pedestrian–car interaction; non-signalized junctions

1. Introduction

Emergencies triggered by natural disasters that can trigger time-critical mass evacuations, such as the impending Tokai, Tonankai, and Nankai earthquakes and their associated tsunamiis [1–3], can cause a wide range of uncommon conditions such as non-functioning traffic signals, debris-scattered roads, pedestrians on main roads, and low lighting. Conditions such as traffic signal blackouts can be widespread, as occurred during the 2011 Tohoku Earthquake and Tsunami [4]. These uncommon conditions can seriously hamper the progress of evacuation, prompting the need for extensive studies using advanced numerical models. Due to their low computational cost and simplicity, simple models [5,6] are widely used for tsunami evacuation simulations. Although such simple models can capture common scenarios such as traffic or pedestrian congestion reasonably well, they are either ineffective or incapable of modeling uncommon yet vital scenarios such as debris-scattered roads and pedestrians and cars at a junction with broken traffic signals. A versatile and powerful alternative approach is Agent-Based Models (ABMs) equipped with fully autonomous agents [7]. Once software agents with sufficient capabilities to reproduce the fundamental behaviors of real evacuees’, such as speed vs. density characteristics, are developed, ABMs can be utilized to model different combinations of these uncommon scenarios as an emergent phenomenon of the agents’ interactions.
Probably driven by the industrial demand to ensure the fire safety of closed spaces, such as high-rise buildings and underground shopping malls, sophisticated ABMs such as EXODUS and EGRESS2002 have been developed; ref. [8] provides a detailed list of the available ABMs for indoor evacuations. Unlike indoor applications, simple models are widely used for large-scale tsunami evacuations [5,6,9], probably due to the complex conditions involved in tsunami evacuations and the computational challenges posed by the large number of evacuees and the size of the domain. Though simple ABMs capture the heterogeneous actions of evacuees, their agents are not fully autonomous. As an example, to ensure that the evacuation time of each agent is realistic, the speed of each agent is externally controlled according to a given fundamental diagram (i.e., speed vs. density relation) [5,6]. This lack of full autonomy of the agents makes simple models either ineffective or incapable of modeling important scenarios such as interruptions to traffic and pedestrians due to the debris scattered on roads and the vehicles and pedestrians at non-signalized junctions. Detailed accounts of autonomous agents for simulating tsunami evacuations are found in [4,7,10]. Several publications have proposed autonomous agents capable of reproducing fundamental diagrams for pedestrians [11–13] and different models of vehicles [14]. Furthermore, the interactions of different modes of evacuation have been studied by [15,16]. It is rare to find vehicle–pedestrian interaction models at non-signalized junctions, and even the existing vehicle–vehicle interaction models, which are mostly based on collision avoidance algorithms [17–22], scheduling schemes [23], and game theory [24], do not reproduce realistic trajectories and speed profiles. According to authors knowledge, only Tomoyuki et al. [4] have attempted to simulate car–pedestrian mode tsunami evacuation during a traffic signal blackout. They have used an agent-based modeling platform called Artisoc 4.0, in which agents’ speeds are set according to a suitable fundamental diagram (i.e., agents are not fully autonomous). The free-flow speed of cars at junctions were set to 10 km/h. Their paper does not provide information on how the car trajectories at junctions are modeled and how the cars and pedestrians interact at junctions.

The objective of this paper is to present a model to cover the above-discussed research gap in simulating non-signalized junctions such that important scenarios such as pedestrian–car mode evacuation during a traffic signal blackout can be accurately simulated. Specifically, we present details of how to model car trajectories at junctions and car speeds along those curved trajectories, identify cars and pedestrians on collision paths, accurately calculate the point of collision even for cars on merging trajectories, and estimate the time to collision. These accurate sensing abilities of car and pedestrian agents provides a strong basis on which a desired model of evacuees’ complex behaviors can be implemented. The rapid advancement of High-Performance Computing (HPC) capabilities has made it possible to simulate large domains (e.g., areas of several hundred square kilometers) using such computationally demanding models. However, existing HPC implementations of evacuation simulators have low parallel computing efficiency, and most can accommodate only several tens of thousands of agents; see [11] for a detailed account available for parallel implementations. We implemented the proposed junction model in our existing ABM with high parallel computing efficiency so that large-scale problems can be simulated in a short time.

Our existing HPC-enhanced ABM includes a high-resolution grid model of the environment and complex autonomous agents capable of perceiving the featured in the grid model [25–29]. The agents are equipped with functions to reproduce observed speed vs. density characteristics for pedestrian–pedestrian interaction, car–car interaction, and pedestrian–car interactions [25–27]. In order to meet the high computational demand of the developed agents, our ABM is equipped with an HPC extension that can efficiently simulate tens of millions of agents in several hundreds of square kilometer regions using parallel computers [29–31].

In the proposed new junction model, car trajectories are modeled using third-order B-splines [32] to a sufficient accuracy, and the free-flow speeds of cars at junctions are approximated to match with the observations. The car agents are programmed to accurately calculate the potential points of collision with pedestrians and other cars at junctions and avoid collisions. As a demonstrative application of the developed non-signalized junc-
2. An Agent-Based Model for Evacuation Simulation

The developed ABM consists of a high-resolution grid to capture the features of the environment, a graph of the topological connectivity of the traversable spaces of the grid, and autonomous agents mimicking the evacuees. The resolution of the grid is decided such that it approximates the simulated domain to a sufficient accuracy, and the grid is updated at suitable time intervals according to the physical disaster being simulated.

Let $A = \{a_i | i = 1, \ldots, n\}$ be a set of $n$ number of agents, and the $i$th agent be defined as $a_i = \{s_i, f_i\}$, where $s_i$ and $f_i$ represent the $i$th agent’s state and update function, respectively. $s_i = \{s^{pub}_i, s^{vis}_i\}$, where $s^{pub}_i$ consists of states, such as speed, walking direction, size, gender, and age category, that can be observed or deduced by fellow evacuees, and the $s^{vis}_i$ consists information that are not deducible by or inaccessible to the fellow agent unless communicated, such as its past experiences, its target destination, and route. Similarly, $f_i = \{f^{pub}_i, f^{vis}_i\}$, where $f^{pub}_i$ consists of functions to exchange information with the neighboring agents, while the rest, such as decision making and moving, compose the private part $f^{vis}_i$. Let the state of the simulated physical domain at time $t$ be represented by $E(t)$, $E^{vis}(t) \subseteq E(t)$ be the region of the environment visible to the agent $a_i$ at time $t$, and the public states of all the agents visible to $a_i$ be $\bar{S}_i \equiv \{s^{pub}_i | i \neq j\}$. Then, the discrete time evolution of $a_i$ can be expressed as:

$$s_i(t + \Delta t) = f_i(s_i(t), E^{vis}(t), \bar{S}_i(t), t).$$

The time evolution of the agents do not make them hop from cell-to-cell like in cellular automata. Instead, agents can freely move across grid cells, updating their positions as $x^{a\Delta t} = x^{a\Delta t} + \Delta t v^{a\Delta t}$, where $x^{a\Delta t}$ and $v^{a\Delta t}$ are the position and velocity of agent $a$ at time $t$.

2.1. Hybrid Model of the Environment

Though a sufficiently high-resolution grid can capture the physical details of the simulated region, grid data structures are computationally inefficient in path planning, storing agents experiences with reference to the spatial locations such that those experiences can be efficiently included in the decision-making process of the agents. To address these weaknesses of the grid data structures, the environment is modeled as a hybrid of a grid $G$ and a graph $L$, and the strengths of these data structures are exploited to efficiently simulate hundreds of square kilometers size domain in high resolution. A two-dimensional (2D) Cartesian grid $G = \{g_{ij}(t) | i, j \in \mathbb{N}\}$ approximates the state of the physical environment, where $g_{ij}(t)$ defines the state of the grid cell $(i, j)$ at time $t$. Connectivity of the traversable spaces in the grid is abstracted by a bidirectional graph $L = G(L, V)$, where $L = \{l_i | i \in \mathbb{N}\}$ and $V = \{v_i | i \in \mathbb{N}\}$ are the sets of links and nodes. Each link $l_i$ contains physical characteristics such as the width and length of $l_i$, number of vehicle lanes, and allowed flow directions. Furthermore, statistics, such as the number of agents passed and their average speeds, are collected to each link.

Even though the grid is updated according to the physical disaster, neither the connectivity of the graph nor the physical characteristics stored in each link are updated. Therefore,
the graph always contains topological connectivity of an ordinary day, severing as the base map in agents’ decision making. Hence, the discrete time evolution of the environment is defined by \( E(t + \Delta t) = \Lambda(G(t), t) \), where \( \Lambda \) is an external function with which the state of each cell \( g_{ij}(t) \), is updated at suitable time intervals, \( m\Delta t \) (\( m \in \mathbb{N} \)), according to the time evolution of the physical disaster (e.g., the progress of tsunami inundation).

Scanning the grid in high-resolution, agent \( a_i \) recognizes the features and changes of its visible surrounding, and important changes, such as blocked or inundated roads, and stores them in its private state \( s_{prv}^i \) with reference to the links and nodes of the graph. The graph is equipped with various path-planning functions to support agents’ decision-making process. An agent can include its past experiences, such as the list of blocked paths it encountered and the statistics collected to graph links, in its decision making to avoid crowded or blocked routes PRIMA [28].

2.1.1. Agents’ Update Function—\( f \)

The agents’ update function \( f \), which defines the agents’ capabilities, is composed of a set of basic constituent functions \( \{g\} \); \( f = g^1 \circ g^2 \circ \ldots \circ g^m \). Some of the constitutive functions we have implemented are briefly explained below.

\( g_{\text{see}} \): Scans the grid \( G \) around an agent’s current location in high resolution and creates the boundary of visibility (see Figure 1) [25]. The scanned distance is equal to the agent’s sight distance, which can be 50 m or longer depending on an agent’s physical abilities;

\( g_{\text{identify}_\text{env}} \): Analyzes the visual boundary and extracts features such as open paths and obstacles [25];

\( g_{\text{navigate}} \): Chooses a suitable open path based on the obstacles and openings identified in \( g_{\text{identify}_\text{env}} \) and the route followed by the agent [25]

\( g_{\text{identify}_\text{inter}} \): Recognizes neighbor agents to interact with, based on visibility and interaction radius;

\( g_{\text{coll}_\text{av}} \): Finds a collision-free walking direction along which an agent can move closer to its preferred speed for a given minimum period of comfortable time \( t_{\text{comfort}} \) to reach the opening chosen in \( g_{\text{navigate}} \), evading collision with the neighbors identified in agents \( g_{\text{identify}_\text{inter}} \). The preferred comfortable time \( t_{\text{comfort}} \) and other parameters are tuned to reproduce observed fundamental diagrams [25,26];

\( g_{\text{path}_\text{planning}} \): Finds paths with desired characteristics [27];

\( g_{\text{is}_\text{path}_\text{blocked}} \): When navigating in a damaged environment, analyzes the data from \( g_{\text{see}} \) to identify whether the desired path is blocked [27];

\( g_{\text{find}_\text{and}_\text{follow}} \): Finds a suitable agent and follows it, if the environment is not familiar;

\( g_{\text{side}_\text{walk}} \): Use pedestrian side walks, when available;

\( g_{\text{car}_\text{at}_\text{signalized}_\text{junction}} \): Control the movement of car agents at junctions obeying traffic signals, maintaining safe distances with cars and pedestrians on potential collision courses, and maintaining safe speeds according to the curvature of trajectory;

\( g_{\text{car}_\text{at}_\text{unsignalized}_\text{junction}} \): Extended version of \( g_{\text{car}_\text{at}_\text{signalized}_\text{junction}} \) without centralized flow control by traffic lights to enable cars move at non-signalized junctions;

\( \ldots \): etc.;

\( g_{\text{execute}_\text{actions}} \): Executes desired actions such as move;

\( g_{\text{update}} \): Updates an agent’s state.
The white-colored, partially circular boundary in Figure 1 shows the boundary of visibility produced by the constituent function $g_{\text{see}}$ of a pedestrian agent. Each individual agents scan its surrounding in a similar manner to identify available paths, obstacles, and visible neighboring agents. Agents store obstacles or important experiences in their memory with respect to the corresponding link or node of the graph $G$ so that those experiences can be taken into account in future decision making.

![Figure 1. An example of the grid and graph environment with a snapshot of agents’ movements at a junction. Blue and black arrows indicate instantaneous velocities of pedestrians and cars, respectively. Pedestrian agents walk along the edges, if the road can accommodate vehicles.](image)

2.1.2. Agents’ Specializations

Since it is impractical to specialize every $f_i$ and $s_i$, we first generate a set of template $\{a^\tau\}$ which are composed as $a^\tau = \{f^\tau, s^\tau\}$. $f^\tau$ and $s^\tau$ are defined according to the role of the agent subgroup $\tau$. As an example, agent subset $a_{\text{police}}$ is defined by designing a suitable $f_{\text{police}}$ to mimic a police officer during an emergency evacuation. Furthermore, police officers with different physical abilities are defined by randomly setting the variables in $s_{\text{police}}$ according to a suitable distribution. Short descriptions of four types of implemented agents are given below.

$a_{\text{resident}}$: Represents a local resident of the simulated area. To mimic the familiarity of the living neighborhood, $s_{\text{resident}}$ possess a mental map of the environment (i.e., access to $G$ and most path finding algorithms) and uses $g_{\text{path_planning}}$ to find paths according to its desired constrains and past experiences. Additionally, they know the locations of possible evacuation areas.

$a_{\text{visitor}}$: Represents non-resident people in the interest area. They do not possess any additional information of the environment aside what they can visually perceive (i.e., $g_{\text{see}}$). Their main evacuation mechanism is to seek a visible high ground or follow other evacuees using $g_{\text{find_and_follow}}$.

$a_{\text{car}}$: Represents multiple people (one or more evacuees) traveling by a car. $s_{\text{car}}$ possess a mental map of the environment, and equipped with logic to drive through non-signalized junctions, avoiding collisions with pedestrians and other cars.

$a_{\text{official}}$: This type of agent represents figures of authority, such as law enforcement and event staff. Their main task is to facilitate fast and smooth evacuation by independently or collectively planning the areas to be covered by each with $g_{\text{path_planning}}$ and commanding or delivering information to other agents with $g_{\text{deliver_message}}$. $s_{\text{officials}}$ also possess a mental map of the environment which can be updated through communication.

3. Simulation of Non-Signalized Junctions

As mentioned in the introduction, conditions such as traffic signal blackouts and pedestrians crossing junctions without respecting traffic signals can be widespread during tsunami-triggered mass evacuations. Specially designed ABMs consisting of agents that are capable of autonomously sensing the presence of these uncommon conditions and mimicking respective actions of evacuees as emergent behaviors are necessary to simulate these uncommon scenarios. While our collision-avoid algorithm [25,30] enables us to simulate
vehicle–pedestrian interactions on straight roads, a few extra functionalities are required to model vehicle–vehicle and vehicle–pedestrian interactions at non-signalized junctions. The rest of this section presents some details of the required additional functionalities, such as approximating trajectories and speed profiles of cars at junctions and car–pedestrian interactions at non-signalized junctions.

3.1. Approximating Vehicle Trajectories at Intersections

Our analysis of vehicle trajectory observations by Alhajyaseen et al. [33] showed that vehicle trajectories at most common intersection geometries, except U-turns, can be approximated using B-spline [32] with knot vector \([0, 0, 0, 1, 1, 1]\). The required three B-spline control points can be easily defined: (1) the lane center at the entry to intersection, (2) the intersection point between center lines of the incoming and outgoing lane, and (3) lane center at the exiting point (see Figure 2a). Comparison with the average of the trajectories observed by Alhajyaseen et al. [33] shown in Figure 2b indicates that our B-spline approximation deviates by only a few centimeters, which is negligible for this particular application. As shown in the same figure, though we found that the trajectories can be more accurately approximated using NURBS, B-spline is preferred since the points along vehicle trajectories can be efficiently calculated with B-splines compared to NURBS.

![Figure 2. Comparison of the average of the trajectory observations by Alhajyaseen et al. and our B-spline and NURBS approximations. The source of the background image of Suemori Dori 2 intersection in Nagoya is Google Maps. (a) Green color points and dashed lines shows the control net of the third-order B-spline for approximating vehicle trajectories. (b) Comparison of third-order B-Spline and NURBS approximations with the observations by Alhajyaseen et al. [33].](image)

Although the evaluation of points along B-splines is efficient, computing the intersecting points of B-splines, which is necessary to prevent collisions of car agents on intersecting trajectories, is computationally expensive [34,35]. A further computationally expensive task is finding the points at which two merging trajectories come close enough for two cars traveling their own trajectories come into contact. This latter calculation is necessary to prevent the collision of car agents on merging trajectories (see Figure 3a). A computationally cheap alternative is to approximate the B-spline as a piece-wise linear curve, using a sufficient number of points on a B-spline curve. Piece-wise linear approximation makes it computationally cheap to compute the potential points of collision on intersecting or merging trajectories. We found that 12 points provide sufficiently accurate results. We automated the construction of car trajectories at junctions of different configurations such that the junction trajectories of cars for a large domain can be automatically constructed. Figure 4 illustrates the main steps involved in the automated generation of the car trajectories at junctions. Figure 5 shows our B-spline approximations for junctions of different configurations.
Figure 3. Illustration of potential collision points of cars with neighboring cars and pedestrians: (a) Potential collision points of cars on different trajectories and safe distance to decelerate; (b) Potential collision points of a car with pedestrians.

Figure 4. Main steps involved in automated construction of car trajectories at junctions: (a) Road center lines (input), (b) B-spline control net, (c) B-spline model of vehicle trajectories, (d) Points on the B-splines for piece-wise linear approximation, (e) Approximate intersecting points of B-splines, (f) Piece-wise linear approximations of B-splines shown with the grid.

Figure 5. Examples of B-spline approximations of junctions with configurations.
3.2. Free-Flow Speed of Cars at Intersections

As well as accurate trajectories, the setting of realistic free-flow speed $s_{ff}$, which is the preferred speed of a driver when there is no danger of collision with vehicles or pedestrians, along these curved trajectories is essential to accurately model car–car interactions and car–pedestrian interactions. Since the speed of cars is one order of magnitude large compared to pedestrians, unrealistic or sudden changes of car speeds can make pedestrian agents behave abnormally. According to Dias et al. [36], the speed profiles of vehicles can be approximated with fifth-order polynomial curves. While their approximation requires field observations, we use the following third-order polynomial approximation, which can be defined with three known parameters and one constraint:

$$s_{ff}(r) = 4(s_d - s_a)r^3 + 4(2s_a - s_m - s_d)r^2 + (4s_m - 5s_a + s_d)r + s_a,$$

where $r$ ($0 \leq r \leq 1$) is the fraction of the distance traveled along a curved trajectory of length $L$. As for the constraint, we assumed that the acceleration is zero (i.e., $\frac{ds_{ff}}{dr} = \frac{ds_{ff}}{dr} = 0$) at the point of the highest curvature where a car reaches the minimum speed of $s_m$, which can be considered as the maximum allowable speed to prevent accidents due to centripetal force. $s_a(= s_{ff}(0))$ and $s_d(= s_{ff}(1))$ are the approaching speed and the desired departing speed. The above equation is derived assuming the maximum curvature is at $r = \frac{L}{2}$, and it is straightforward to derive it for general cases.

We found that this simple approximation can reasonably reproduce the observed speed profiles of cars at junctions as shown in Figure 6. The whisker-box plot in Figure 6 shows the field observations provided by Prof. Hideki Nakamura, Nagoya University. The lines and × marks show the simulation results; lines indicate the speeds of car agents within the junctions, and × marks include the deceleration and acceleration during the approach and departure. The above equation defines only the free flow speed, and if a car agent detects potential collision with other cars or pedestrians, it decelerates to a speed $s < s_{ff}$ to prevent collision, and accelerates back to $s_{ff}$ once it is clear of any collisions.

![Figure 6. Comparison of free-flow speeds of thee car agents and field observations by Professor Hideki Nakamura.](image)

3.3. Agent Interactions at Non-Signalized Junctions

Modeling the cars’ and pedestrians’ movements at a signalized junction is relatively simple since the traffic lights provide a centralized control. On the other hand, the absence of centralized controlling makes it significantly difficult to model non-signalized junctions. This subsection briefly explain the modeling of car–car and car–pedestrian interactions at non-signalized junctions, in which we assume the following:

- Evacuees do not panic;
- Cars do not deviates from the trajectories presented in Section 3.1;
- Each car observes neighboring cars’ and pedestrian agents’ positions and their turn signals and estimates their relative speeds and moving directions;
• If a car identifies a potential collision with a car or pedestrian, it avoids collision by applying comfortable deceleration to maintain a safe distance;
• Pedestrian agents also change the speed and moving directions to prevent collision with car agents.

3.3.1. Car–Car Interactions at Non-Signalized Junctions
The implemented algorithm to resolve collision at non-signalized junctions is somewhat complicated. However, it is based on the simple rule that all the cars obey a given common priority. In our current implementation, the car to first arrive at the point of collision is given priority to move uninterrupted by the others. This target priority can be changed as desired.

We classify car–car interactions at a junction to three groups; intersecting trajectories (e.g., V1 and V3 in Figure 3a), diverging trajectories, and merging trajectories (e.g., V2 and V4 in Figure 3a). The points of collisions are defined as the locations at which two cars of given dimensions traveling on the same or different trajectories come into contact. In case of merging trajectories, once the cars V2 and V4 in Figure 3a enter the merged road, they drive while maintaining a safe gap between them. The safe gap between two vehicles is calculated considering time to decelerate including driver’s reaction time, and an additional safe distance which is set to be the length of a car $d_s$. Figure 7 shows snapshots of two streams of cars merging at a junction.

3.3.2. Car–Pedestrian Interaction
In Japan, walking is the recommended way of evacuating, and hence we programmed the car agents to give priority to pedestrians. First, a car agent estimates the distance $d$ that it would travel before stopping under a comfortable deceleration, and identifies the pedestrian agents, shown in red color in Figure 3b, occupying its projected curved path of length $d$. In addition, the car agent calculates which of the pedestrian agents can enter its projected path of length $d$ and the point of potential collision, according to their relative speeds. Then, the car decelerates to avoid these potential collisions. Although the same basic logic is involved in car–pedestrian interaction on straight roads, the curved trajectories at junctions makes it somewhat complicated.
4. Demonstrative Application

As a demonstrative application of the presented model of non-signalized junctions, we simulated a hypothetical evacuation scenario in a coastal city shown in Figure 8. It is assumed that emergency evacuation was advised at 11 p.m., and a total of 61,218 people are expected to evacuate to above 10 m elevation. Assuming most of the people were at home, the agents are initialized closer to the buildings, setting the number of agents around each building according to its floor area.

Figure 8. Grid and graph of 9.6 km × 5.4 km coastal region used for the demonstrative simulation. (a) 1 m × 1 m resolution grid, (b) Graph.

While the recommended mode of evacuation is walking, significant use of cars was observed during past major tsunamis such as 2011 Great East Japan Earthquake. Initiated by this use of cars, it is often discussed how many needy people can be allowed to use cars without negatively affecting the expected progress of pedestrian-mode evacuation. To quantitatively evaluate the effect of allowing the needy (e.g., elderly, expecting mothers, etc.) to use cars for evacuation, we made a given $p$ percentage of slow-moving people use cars, assuming each car carries three persons. The slowest people living at least 1 km away from the nearest evacuation were converted to cars. We considered the following five scenarios. In the rest of this section, we refer to these scenarios by the number in the following list:

1. All the evacuees walk;
2. 6% of the slowest were allowed to use cars; total of 1224 cars;
3. 9% of the slowest were allowed to use cars; total of 1836 cars;
4. 15% of the slowest were allowed to use cars; total of 3060 cars;
5. 15% of the slowest were allowed to use cars, and some roads were restricted either only to pedestrians or cars to reduce the interactions between them.

The statistics of the evacuation start time, speeds, and the distance to closest evacuation area of the pedestrian and car agents, for the scenario with 6% cars users, are shown in Figures 9 and 10. Due to the relatively small number of cars, all five scenarios have similar distributions. Since we considered a nighttime evacuation, we assumed that people preferred to walk on roads wider than 4m; the pedestrian agents are allowed to use roads of any widths, but they are programmed to give higher preference to use wider than 4 m roads when available [28]. Furthermore, we assumed that the earthquake had rendered the traffic signals non-functioning, and the non-signalized junction models presented in the Section 3 was used to model the car–car and car–pedestrian interactions on roads and at the junctions. In all the scenarios, evacuation areas for car agents were separated from pedestrians to prevent congestion at the entrances to evacuation areas, and the number of cars to each evacuation area were controlled to reduce long traffic jams and limit the number according to the available parking area. While in the first four scenarios, agents were allowed to choose the closest evacuation area without any restriction of their routes of choice, in the fifth scenario, we restricted some road stretches such that either only cars or pedestrians travel along those road stretches. However, at junctions, pedestrians (cars) were allowed to cross a road dedicated for cars (pedestrians). We expected that these restrictions of road usage would reduce the friction between cars and pedestrians, making it possible
to use large number of cars. In addition, in all the scenarios, car agents were forced to start evacuation within the first 20 min from the time of tsunami warning (see Figure 9b). This latter settings mimic the restriction of evacuation start time window for the car users, as a strategy of reducing interactions between cars and pedestrian mode evacuees.

Figure 11 compares each scenario’s progress of evacuation. According to Figure 12c, when no cars are allowed, a small percentage of the population could not reach a safe shelter. This small percentage is the slow-moving people who were more than 1 km away from the nearest safe area. Allowing 6% of the population to use cars enables these slow-moving (the needy) evacuees to reach a safe shelter, achieving 100% within 60 min. Furthermore, the 6% car users scenario has slightly accelerated the evacuation progress. Though the increases in the number of car users to 9% and 15% have accelerated the progress during the first 30 min, the arrival of a large number of pedestrians significantly hinders the progress of cars roughly between the 30 and 50 min period (see Figure 11b). We observed that the pedestrians significantly influenced the cars both along the roads and at junctions.

In scenario 5, we tried to reduce this pedestrian interruption to traffic flow by restrict- ing the usage of some stretches of roads either only to pedestrians or cars. However, this restriction is flexible. If a car or a pedestrian is initialized along any of these restricted roads, it is allowed to use the restricted roads until it reaches an unrestricted area. Furthermore, pedestrians (cars) are allowed to cross any of the restricted roads at junctions. Hence, enforced restrictions do not completely eliminate the car–pedestrian interactions. As seen in Figure 11b, this restriction dramatically improves the evacuation progress, making most of the evacuees reach a shelter within 60 min. Though the progress of this scenario is slower compared to 6% and 9%, its performance is comparable to the scenario with no cars, indicating that a large number of cars can be allowed if well planned.

The Figure 13 compares the number of pedestrians and cars walked along each road. According to Figure 13a,b, the changes in pedestrians are minor and localized to the center of the city. On the other hand, Figure 13c,d indicate that the routes of the cars have significantly changed, and the cars were forced to travel longer to reach a shelter. As seen in Figure 10, the distances traveled by pedestrians have not changed much from the scenario with 6% of car users, while a significant number of car users were forced to travel to shelters located more than 3 km away. Since less pedestrians were on the
suburban roads, the progress of the cars moving to farther shelters were not hindered. Furthermore, Figure 12 compares the statistics of each agent’s characteristic speed and the average speed calculated as the ratio of the distance traveled and time taken to reach its destination. The differences between the characteristic and actual average speeds of pedestrians are negligible, probably because of their high mobility and the priority given at the junctions. On the contrary, the estimated average speeds of cars are drastically different from their characteristic speeds. This is expected, since cars cannot travel at their characteristic speed all the time; cars have to slow down at junctions, even if the roads are empty, and pedestrians significantly slow the cars at junctions and along the roads. Figure 12f shows that a large number of cars in scenario 4, which has 15% cars, is almost stagnant, while Figure 12h shows that the route restrictions in scenario 5 significantly improved the progress of cars. The estimated average speed of cars in scenario 5 with 15% car users is almost close to that of the scenario with 6% car users.

Figure 10. Histograms of the distance to the closest evacuation area for the scenario 3 and 5: (a) Pedestrians (6% car users), (b) Cars (6% car users), (c) Pedestrians (15% car + route restrictions), (d) Cars (15% car users + route restrictions).

Figure 11. Cont.
Figure 11. Comparisons of evacuation progress under each of the five scenarios considered: (a) Total progress, (b) Progress of cars, (c) Progress of pedestrians.

Figure 12. Cont.
Figure 12. Speeds of pedestrian and car agents. Black indicates the theoretical maximum assuming the agent moves at its maximum speed, and blue indicates the average speed of the simulation. (a) Speed of pedestrians (6% car users), (b) Speed of cars (6% car users), (c) Speed of pedestrians (9% car users), (d) Speed of cars (9% car users), (e) Speed of pedestrians (15% car users), (f) Speed of cars (15% car users), (g) Speed of pedestrians (15% car + route restrictions), (h) Speed of cars (15% car + route restrictions).

Figure 13. Routes taken by pedestrians and cars for the last two scenarios with 15% car users: (a) Pedestrians (15% car users), (b) Pedestrians (15% car users+route restrictions), (c) Cars (15% car users), (d) Cars (15% car users+route restrictions).

5. Discussion

According to the Disaster Management Bureau of the Cabinet Office of Japan, there is a 70–80% likelihood that magnitude 8–9 scale earthquake will occur in the area along Nankai Through as of 2021 [2,3]. The Central Disaster Management Council of Japan estimates that some coastal areas, which are highly populated, would be inundated within 20–30 min after the earthquake [3]. Long distances to the closest evacuation area due to relatively flat terrain, a significant percentage of elderly population, short tsunami arrival time, and the
significant car usage during the 2011 Tohoku Tsunami have prompted policy makers to allow a certain number of cars to ensure the safety of the needy people (e.g., sick, elderly, families with infants), though the current recommended mode of evacuation is walking [4]. Extensive traffic jams [37,38] observed during the 2011 Tohoku Tsunami emphasizes that allowing cars requires careful planning considering wide range of hampering conditions caused by the preceding mega-earthquake.

Widespread traffic signal blackouts were reported during the 2011 Great East Japan Tsunami [4], and hence, pedestrian–car mode evacuation during a traffic signal blackout at night is an important scenario in evaluating the usage of cars. Simulating such uncommon conditions caused by earthquakes demands specialized simulators with capabilities to accurately model the space of the environment and agents with functionalities to accurately sense their environment in high-resolution. As discussed in the Section 1, to the best of our knowledge, existing evacuation simulators are not capable of simulating the interactions between pedestrians and cars at non-signalized junctions. Section 3 of this paper presented a high-resolution model to cover this research gap.

Our ABM models the environment at $1 \times 1 \text{m}^2$ or higher resolution enabling us to accurately model the space at junctions. Comparing with observations by Alhajyaseen et al. [33], we demonstrated that car trajectories at junctions can be approximated to a sufficient accuracy using third-order B-splines. Although we found that car trajectories could be more accurately approximated by NURBS, we choose third-order B-splines since the required control points were easy to define. We automated the generation of car trajectories since it is impractical to manually define those at tens of thousands of junctions in large scale simulations. A disadvantage of B-splines and NURBS is the difficulty of computing the intersection points of curved trajectories [34,35]. We addressed this by approximating the B-spline curves as a piece-wise linear curve; 12 linear segments are found to produce sufficient accuracy for the target application. A limitation of third-order B-splines is their inadequacy to accurately approximate U-turns and trajectories involving double curvatures. Higher-order B-splines or NURBS can be used to overcome this limitation.

We approximated the free-flow speed of cars at junctions using a cubic polynomial parameterized with the distance along the respective third-order B-spline trajectories. Comparisons with Prof. Nakamura’s observations demonstrated that our third-order parametric function could approximate the free-flow speed of cars at junctions reasonably well. Our third-order approximation is based on the assumption that the acceleration with respect to the distance traveled is zero at the point of maximum curvature. Instead of this zero-acceleration condition, we can use the maximum allowable centrifugal force along the curved trajectories to obtain a more realistic approximation for free-flow speed. An analytical expression for the centrifugal force along the third-order B-splines trajectories can be easily derived, making it practical to use this important physical constraint to define the free-flow speed.

At junctions, agents use their high-resolution scanning functionality to identify fellow agents on potential collision paths and decelerate or change directions to avoid collisions according to a desired set of rules and priorities. The assumption that car agents do not deviate from their B-spline trajectories enables the car agents to accurately identify collision-prone car and pedestrian agents, calculate the points of potential collisions with them, accurately estimate the time to reach the point of collision, even considering the free-flow speed along the B-spline trajectories, and accurately calculate the required deceleration to maintain a safe gap with the collision-prone agents. Our current model uses the simple rule that the car agent first to arrive at the potential point of collision travels uninterrupted, while the other collision-prone cars decelerate to maintain a safe distance. Furthermore, we programmed the car agents to give priority to pedestrians with respect to the fact that the recommended mode of evacuation is walking. While the current model is based on these simple rules to resolve potential collisions, the high-resolution sensing capabilities of agents introduced by the new junction model provide a strong basis on which more
sophisticated priorities and collision-avoiding rules can be implemented to accurately mimic the real world.

It should be emphasized that each car agent independently makes the decisions, such as which car should proceed uninterrupted, and no centralized control is involved. The decentralized decision-making significantly simplifies the parallel computing algorithms. However, in rare occasions when two or more cars have the same arrival time to the point of collision, this decentralized decision of car agents leads to deadlocks. Once a deadlock is detected, we either introduce small random perturbations to their speeds or allow the car with the lowest ID to continue uninterrupted. The assumption that cars do not deviate from their B-spline trajectories is not applicable when debris are assumed to be scattered over the roads. This is the major weakness of the implemented junction model, and more sophisticated algorithms have to be developed to simulate debris scattered junctions.

Due to the lack of prior studies on car–pedestrian interactions at non-signalized junctions and difficulties in finding suitable field observations of car–pedestrian interactions during traffic signal blackouts, we could neither verify nor validate the implemented responses of car and pedestrian agents for simulating car–pedestrian interactions during traffic signal blackout. Only interaction modules responsible for pedestrian–pedestrian, car–car, and car–pedestrian interactions on roads have been validated by comparing with field observations. We restrict ourselves from making a detailed discussion on the results presented in previous section, since a detailed analysis of the results from a non-validated module can lead to premature conclusions.

Simulating hypothetical evacuation scenario involving mixed car–pedestrian mode evacuation, we demonstrate that the use of a certain percentage of cars can be beneficial, provided that mainly the needy are allowed to use cars, and the time window for the cars’ usage is restricted. According to simulated scenarios, increasing the number of car users beyond 6% with no restrictions of route choices increasingly degraded the evacuation progress. However, we observed that strategically restricting some road stretches only to cars or pedestrians to reduce the friction between cars and pedestrians can accommodate a large number of car users without degrading evacuation progress. While the routes were restricted manually in the presented scenario, significantly better performing route restrictions could be found using a suitable optimization algorithm [28]. Although the developed code must be thoroughly validated before any practical applications, the presented demonstrative scenarios indicate that a significant number of the needy can be allowed to use cars for evacuation if their routes and evacuation start time window are strategically planned.

6. Concluding Remarks

In coastal regions located at close proximity to subduction zones, mega-thrust earthquakes can cause various uncommon conditions such as traffic signal blackouts and debris on roads, hindering the progress of evacuation from any succeeding tsunami. A lack of ABMs to accurately model the interactions of pedestrians and cars during a traffic signal blackout is one major problem in evaluating various strategies involving car usage to accelerate evacuation process. To cover this research gap, we presented a high-resolution model of junctions. Car trajectories at various junction configurations are approximated using B-splines to a sufficient accuracy and free-flow speed along the curved trajectories are approximates using cubic parametric functions. Assuming the cars do not deviate from the B-spline trajectories, the proposed model provide accurate calculations of points of potential collision with other agents, time to reach the point of collision, and required deceleration to maintain a safe distance. These provide the necessary basis for implementing more complex evacuees’ behavior to mimic the real world. A lack of high-resolution observations is a major barrier in validating implemented agents’ actions at a non-signalized junctions. Considering the number of lives exposed to fatal danger, collecting data to validate micro-level models for simulating uncommon conditions is important in finding strategies to accelerate evacuation progress.
References

1. Goda, K.; Yasuda, T.; Mori, N.; Muhammad, A.; De Risi, R.; De Luca, F. Uncertainty quantification of tsunami inundation in Kuroshio, Kochi Prefecture, Japan, using the Nankai–Tonankai megathrust rupture scenarios. Nat. Hazards Earth Syst. Sci. 2020, 20, 3039–3056. [CrossRef]

2. Disaster Management Bureau, Cabinet Office, The Government of Japan. Disaster Management in Japan. 2021. Available online: http://www.bousai.go.jp/1info/pdf/saigaipamphlet_je.pdf (accessed on 13 March 2022).

3. Goda, K.; Yasuda, T.; Mai, M.; Maruyama, T.; Mori, N. Tsunami simulations of mega-thrust earthquakes in the Nankai–Tonankai Trough (Japan) based on stochastic rupture scenarios. Geol. Soc. Lond. Spec. Publ. 2017, 456, 55–74. [CrossRef]

4. Takabatake, T.; Fujisawa, K.; Esteban, M.; Shibayama, T. Simulated effectiveness of a car evacuation from a tsunami. Int. J. Disaster Risk Reduct. 2020, 47, 101532. [CrossRef]

5. Goto, Y.; Affan, M.; Agussabti; Nurdin, Y.; Yulian, D.K.; Ardinasihya. Tsunami evacuation simulation for disaster education and city planning. J. Disaster Res. 2012, 7, 92–101. [CrossRef]

6. Imamura, F.; Muhari, A.; Mas, E.; Pradono, M.H.; Post, J.; Sugimoto, M. Tsunami disaster mitigation by integrating comprehensive countermeasures in Padang city, Indonesia. J. Disaster Res. 2012, 7, 48–64. [CrossRef]

7. Wang, Z.; Jia, G. A novel agent-based model for tsunami evacuation simulation and risk assessment. Nat. Hazards 2021, 105, 2045–2071. [CrossRef]

8. Kuligowski, E.D; Peacock, R.D.; Hoskins, B.L. Technical Note. In A Review of Building Evacuation Models, 2nd ed.; National Institute of Standards and Technology, U.S. Dept. of Commerce. Available online: https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=906951 (accessed on 29 March 2022).

9. Shimamoto, H.; Schmöcker, J.; Nagao, B.; Nakamura, T.; Uno N.; Yamazaki, H. Evaluation of tsunami evacuation planning considering vehicle usage and start timing of evacuation. Transp. A Transp. Sci. 2018, 14, 50–65. [CrossRef]

10. Mas, E.; Koshimura, S.; Imamura, F.; Suppasri, A.; Muhari, A.; Andriano, B. Recent advances in agent-based tsunami evacuation simulations: Case studies in Indonesia, Thailand, Japan and Peru. Pure Appl. Geophys. 2015, 172, 3409–3424. [CrossRef]

11. Makinoshima, F.; Imamura, F.; Abe, Y. Enhancing a tsunami evacuation simulation for a multi-scenario analysis using parallel computing. Simul. Model. Pract. Theory 2018, 83, 36–50. [CrossRef]

12. Curtis, S.; Manocha, D. Pedestrian simulation using geometric reasoning in velocity space. In Pedestrian and Evacuation Dynamics; Springer: Cham, Switzerland, 2012; pp. 875–890.

13. Sahil, N.; Andrew, B.; Sean, C.; Manicha, D. Generating pedestrian trajectories consistent with the fundamental diagram based on physiological and psychological factors. PLoS ONE 2015, 10, e0117856. [CrossRef]

14. Rakha, H.; Gao, Y. Calibration of steady-state car-following models using macroscopic loop detector data. In 75 Years of the Fundamental Diagram for Traffic Flow Theory. Greenshields Symposium; Transportation Research Board: Washington, DC, USA, 2011; Volume 149, pp. 178–198. Available online: https://onlinepubs.trb.org/onlinepubs/circulars/ec149.pdf (accessed on 28 March 2022).

15. Xin, Z.; Gang-Len, C. A mixed-flow simulation model for congested intersections with high pedestrian vehicle traffic flows. Simulation 2014, 90, 570–590.

16. Jiang, R.; Wu, Q.S. The moving behavior of a large object in the crowds in a narrow channel. Phys. A Stat. Mech. Its Appl. 2006, 364, 457–463. [CrossRef]

17. Alonso-Mora, J.; Naegeli, T.; Siegwart, R.; Beardsley, P. Collision avoidance for aerial vehicles in multi-agent scenarios. Auton. Robot. 2015, 39, 101–121. [CrossRef]

18. Berg, J.V.D.; Guy, S.J.; Lin, M.; Manocha, D. Reciprocal n-body collision avoidance. In Proceedings of the Robotics Research: The 14th International Symposium ISRR, Springer Tracts in Advanced Robotics, Lucerne, Switzerland, 31 August–3 September 2011; Volume 70, pp. 3–19.

19. de Campos, G.R.; Falcone, P.; Sjberg, J. Autonomous cooperative driving: A velocity-based negotiation approach for intersection crossing. In Proceedings of the 16th International IEEE Conference on Intelligent Transportation Systems, The Hague, The Netherlands, 6–9 October 2013; pp. 1456–1461. [CrossRef]

20. Doniec, A.; Mandiau, R.; Pieschowiak, S.; Espié, S. Anticipation based on constraint processing in a multi-agent context. Auton. Agents Multi-Agent Syst. 2008, 17, 339–361. [CrossRef]
21. Doniec, A.; Mandiau, R.; Piechowiak, S.; Espi, S. A behavioral multi-agent model for road traffic simulation. *Eng. Appl. Artif. Intell.* **2008**, *21*, 1443–1454. [CrossRef]

22. Fu, Y.; Li, C.; Xia, B.; Dong, W.; Duan, Y.; Xiong, L. A novel warning/avoidance algorithm for intersection collision based on dynamic bayesian networks. In Proceedings of the 2016 IEEE International Conference on Communications, Kuala Lumpur, Malaysia, 22–27 May 2016; pp. 1–6. [CrossRef]

23. Colombo, A.; Vecchio, D.D. Least restrictive supervisors for intersection collision avoidance: A scheduling approach. *IEEE Trans. Autom. Control* **2015**, *60*, 1515–1527. [CrossRef]

24. Mandiau, R.; Champion, A.; Auberlet, J.M.; Espié, S.; Kolski, C. Behaviour based on decision matrices for a coordination between agents in a urban traffic simulation. *Appl. Intell.* **2008**, *28*, 121–138. [CrossRef]

25. Leonel, A.E.M.; Wijerathne, M.L.L.; Hori, M.; Ichimura, T.; Tanaka, S. On the development of an MAS based evacuation simulation system: Autonomous navigation and collision avoidance. *Lect. Notes Comput. Sci.* **2013**, 8291, 388–395.

26. Aguilar, L.; Maddegedara, L. On a Mass Evacuation Simulator with Complex Autonomous Agents and Applications. *J. Earthq. Tsunami* **2016**, *10*, 1640021. [CrossRef]

27. Leonel, A.E.M.; Wijerathne, M.L.L.; Hori, M.; Ichimura, T.; Tanaka, S. A scalable workbench for large urban area simulations, comprised of resources for behavioural models, interactions and dynamic environments. *Procedia Comput. Sci.* **2014**, *108*, 937–947.

28. Leonel, A.E.M.; Wijerathne, M.L.L.; Ichimura, T.; Hori, M. Automatic evacuation management using a Multi Agent System and parallel meta-heuristic search. *Lect. Notes Comput. Sci.* **2016**, *9862*, 387–396.

29. Wijerathne, L.; Petprakob, W.; Aguilar, L.; Hori, M.; Ichimura, T. Scalable HPC Enhanced Agent Based System for Simulating Mixed Mode Evacuation of Large Urban Areas. *Transp. Res. Procedia* **2018**, *34*, 275–282. [CrossRef]

30. Melgar, L.E.A.; Wijerathne, L.; Hori, M.; Ichimura, T.; Tanaka, S. A Scalable Workbench for Large Urban Area Simulations, Comprised of Resources for Behavioural Models, Interactions and Dynamic Environments. *Lect. Notes Comput. Sci.* **2013**, *8861*, 166–181.

31. Aguilar, L.; Maddegedara, L.; Ichimura, T.; Hori, M. On the performance and scalability of an HPC enhanced MAS based evacuation simulator. *Procedia Comput. Sci.* **2017**, *108*, 937–947. [CrossRef]

32. Piegl, L.; Tiller, W. *The NURBS Book*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 1996.

33. Alhajyaseen, W.K.; Asano, M.; Nakamura, H.; Tan, D.M. Stochastic approach for modeling the effects of intersection geometry on turning vehicle paths. *Transp. Res. Part C Emerg. Technol.* **2013**, *32*, 179–192. [CrossRef]

34. Morken, K.; Reimers, M.; Schulz, C. Computing intersections of planar spline curves using knot insertion. *Comput. Aided Geom. Des.* **2009**, *26*, 351–366. [CrossRef]

35. Natarajan, B. K. On Computing the Intersection of B-Splines. In Proceedings of the Sixth Annual Symposium on Computational Geometry, Berkley, CA, USA, 7–9 June 1990; pp. 157–167. [CrossRef]

36. Dias, C.; Iryo, A.; Oguchi, T. Predicting optimal trajectory of left-turning vehicle at signalized intersection. *Transp. Res. Procedia* **2017**, *21*, 240–250. [CrossRef]

37. Ministry of Land, Infrastructure, Transport and Tourism of Japan. Routes, Facility Layouts and Guidance for Tsunami Evacuation. 2013. Available online: http://www.mlit.go.jp/common/000233464.pdf (accessed on 13 March 2022). (In Japanese)

38. Hara, Y.; Kuwahara, M. Traffic Monitoring immediately after a major natural disaster as revealed by probe data—A case in Ishinomaki after the Great East Japan Earthquake. *Transp. Res. Part A Policy Pract.* **2015**, *75*, 1–15. [CrossRef]