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ScienceDirect

Transportation Research Procedia 14 (2016) 2207 – 2216





6th Transport Research Arena April 18-21, 2016

Traffic models for self-driving connected cars

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Abstract

Self-driving and connected vehicles, communicating with one another (V2V technology) and with the road infrastructure (V2I technology), are a subject of extensive research nowadays and are expected to revolutionize the automotive industry in the near future. The major goal of our work is to design a microscopic traffic simulation model for such vehicles, including a robust protocol for exchanging information. The question arises as to whether such communication system may efficiently improve travel quality while reducing the risk of collisions. For the purpose of our research we created and developed a simulation software. Our tool visualizes traffic flow for custom but simplified road maps. The transport infrastructure includes multiple junctions, optionally equipped with traffic lights, and roads with varying number of travel lanes. Each vehicle is assigned a fixed route leading to a randomly chosen destination point. Any decisions made by autonomous cars (regarding acceleration or turning maneuvers) are preceded by communication stages (retrieving necessary data, negotiations). In the paper we present fundamental concepts, assumptions and design of our model and simulation software, we also discuss potential issues relevant to our approach. As for the future work, we plan to implement our model in a large-scale agent-based traffic simulation software, Traffic Simulation Framework, so that further examination will be carried out for realistic road networks taken from the OpenStreetMap project. We also plan to apply machine learning techniques, so that self-driving vehicles, as well as traffic light controllers, will be able to learn how to develop the best strategy and by this way improve traffic safety and efficiency in atypical cases.

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Peer-review under responsibility of Road and Bridge Research Institute (IBDiM)

Keywords: Self-driving cars; connected cars; microscopic traffic model; traffic simulation

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1. Introduction

1.1. Research motivation

Large traffic congestion is an important civilizational and commercial problem, especially in urban, densely inhabited areas. It causes delays in travel time, stress of drivers, noise, problems in organizing public transport and detours, larger air pollution, fuel and energy consumption etc. Drivers in 7 largest polish cities lose yearly approximately 3.6 billion PLN due to traffic jams (Deloitte and Targeo.pl (2014)). The situation is similar in other countries. Drivers in 471 urban areas in U.S. lose yearly 6.9 billion hours (42 hours per auto commuter) and 3.1 billion gallons of fuel (19 gallons per auto commuter), Urban Mobility Scorecard (2015). CEBR (2015) forecasts that the worldwide cost of traffic gridlocks may reach \$293.1 billion by 2030 - almost a 50% increase from 2013.

Another important problem related to vehicular traffic (not only large traffic congestion) is car accidents and their consequences: deaths of passengers, damages of cars etc. According to KGP (2015), there were 34 970 car accidents and 348 028 collisions in 2014 in Poland. As a consequence, 3 202 people died, 42 545 were wounded. According to WHO (2013), worldwide the total number of road traffic deaths is 1.24 million per year, while the number of injuries caused by crashes is more than 20 million. The economic cost of crashes is estimated to be few times larger than the cost of large congestion (Kittelson (2010)). The need for innovative solutions able to decrease traffic congestion as well as number and consequences of crashes arises. According to Google (2015), about 94% of all car accidents in the U.S. involve human error, so eliminating this factor seems to be the best way to reduce the risk of collisions. An innovative solution to do it is introducing autonomous (self-driving) and connected vehicles, capable of driving without any actions of human and communicating with each other (V2V – vehicle-to-vehicle communication) and with the infrastructure (V2I – vehicle-to-infrastructure communication, I2V – infrastructure-to-vehicle communication) in order to ensure traffic safety and smoothness.

Autonomous and connected vehicles are nowadays the area of extensive research. Many companies from automotive and IT industries try to build their own working models of such automobiles. Simultaneously, research efforts are focused on investigating impact of such vehicles on traffic congestion, safety, the society and global economy (Atiyeh (2012), Shladover et al. (2012)). There are premises to suspect that introducing autonomous and connected vehicles may revolutionize the whole transportation area. Thanks to self-driving cars, disabled people, elders or people without valid driver's license, could safely travel to long distances. On the other hand, there may be no more need for a driver's profession or it may look totally different - limited to giving commands and supervising machine. The industry of logistics may change, cargo may be delivered cheaper and faster, especially in case of long distance shipments (there may be no need for long stops for driver's rest). Public and private transportation may change as well, taxis and buses may be replaced by cars on-demand, shared among many passengers, being in motion almost all the time, instantly picking people up on call (thus, this approach may reduce demand for parking places and improve space utilization in urban areas - the need for parking space in the United States may be reduced by more than 5.7 billion square meters, Bertoncello and Wee (2015)). While the total number of cars in motion may increase in some areas (more people will be able and keen to use a car) having negative impact on traffic density and congestion, reduced demand for parking may reduce number of cars driving in the city center (it is estimated that 30% of traffic congestion in downtown areas in big cities is generated by vehicles cruising for unoccupied parking spot, Shoup (2011)). Passengers will be able to spend their travel time working or relaxing.

In addition, thanks to V2V communication cars could potentially exchange information about their positions, speeds, routes, plans for changing speed or lane, turning, stopping. They could let other cars know about their intentions and collaboratively agree on common driving strategies, which would ensure safety and be in some terms optimal for achieving desired goals. It is estimated that self-driving cars could reduce the number of accidents by 90%, saving many lives and yearly about \$190 billion in U.S. (Bertoncello and Wee (2015)). The self-driving revolution is expected to be the greatest thing to happen to public health in the 21st century (GeekWire (2015)).

Moreover, V2I communication may totally replace infrastructure-based sensors being in use nowadays, such as inductive loops, radars, video cameras. Cars could just communicate with the infrastructure and send their positions, speeds, routes and intended maneuvers to the traffic management center, in which powerful servers equipped with realistic maps may build models of the actual traffic situation in real time and run microscopic traffic simulations, much faster than real time, in order to make very accurate, short-term predictions of traffic conditions. Such

simulations may be also used to assess quality of different traffic management strategies, e.g., to find good, (sub)optimal, traffic assignment (setting of routes for all cars), or (sub)optimal configuration of traffic signals (though, it is possible that thanks to V2V communication traffic signals will no longer be necessary). Recommended settings of routes and behaviors could be sent back to cars using I2V communication and applied in reality.

This is just a theoretical idea of how self-driving cars with V2X communication could improve traffic smoothness, safety and other important factors. There are many practical issues to be solved on a way to putting this concept into practice, e.g., designing and deploying the proper infrastructure for traffic detection, V2X communication and running computations. Also, realistic and efficient traffic simulation models for autonomous and connected vehicles need to be constructed. The latter is the main goal of the research presented in this paper. In the past, traffic models were mostly designed to reflect the real traffic with as good accuracy and conformity with reality as possible, on different levels of details: from microscopic level (considering every vehicle as a separate agent, modeling its state, velocity and position) to macroscopic level (modeling relations between aggregated parameters, such as speed, density, flow). Since self-driving cars will be steered by machines which can just run interactive algorithm, their behavior can be modeled and simulated using the same (or similar) interactive algorithms, which may be implemented in machines computationally equivalent to the Interaction Machine (Turing Machine equipped with additional input and output tapes, Goldin (2004), Wegner (1998)). Similarly, microscopic models of self-driving and connected vehicles, tested in the simulation environment, may lead to good interactive algorithms for on-board computers of self-driving and connected cars. Such traffic models may serve to investigate atypical scenarios, e.g., failures of infrastructure components. Thus, designing traffic models for autonomous and connected cars seems to be indispensable step for the further development of this emerging technology.

2. History and state of art

2.1. Autonomous and connected cars

Experiments with autonomous and connected cars have been conducted since at least 1925 (Radio Auto (1925)), when a driverless car was driving on streets of Milwaukee. However, the car was not truly autonomous, it was radiooperated from a second car (this could be considered as a case of V2V communication). The first truly autonomous cars, capable of driving without any human intervention, appeared in the 1980s, being results of pioneering research work conducted by the team of E. Dickmann (Mercedes-Benz van with cameras, sensors and sophisticated computer vision strategies, Dickmann and Zapp (1988)) and, independently, by the team from Carnegie Mellon University (projects NavLav and Autonomous Land Vehicle, Kanade et al. (1986)). Even these first approaches, designed in the era of computers with lower computational power than nowadays, were based on very advanced tools and concepts, such as lidar (remote sensing technology which measures distance by illuminating a target with a laser and analyzing the reflected light), transputer (microprocessor designed for parallel processing), Kalman filters, neural networks. Nowadays, many major automotive manufacturers are testing driverless cars technology. Also, IT companies (e.g., Google (2015), Apple (2015)) and research institutes (e.g., VisLab (2015), Oxford University (2015), FUM (2015)) are working on their models of self-driving vehicles, including also electric power supply. In some U.S. states (e.g., Nevada, Florida, California, Michigan) autonomous cars are already permitted (NCSL (2015), UoW (2015)). Some other countries have allowed testing autonomous cars in traffic as well. There are interesting projects aiming to demonstrate autonomous vehicles potential, e.g., CityMobil2 (2015), Beta City Initiative (2015).

Partially automated cars are already driving on public roads, but are not as advanced as fully autonomous cars. National Highway Traffic Safety Administration, NHTSA (2013), proposes a formal classification of automation, from Level 0 (No automation) to Level 4 (Full self-driving automation). In our research we focus on models in which no driver's control is required, which is Level 4 of automation, but currently we investigate only standard maneuvers, so results of our research may be also applied to automation from Level 3 (Limited self-driving).

Autonomous cars scan the surrounding area to detect other vehicles and obstacles, but the range of such detection is relatively low and on-board computers have to interpret perceived data fast and correctly. Without communication cars cannot obtain detailed information about other vehicles' plans, routes and goals (however, sophisticated

algorithm could make some suppositions) and cannot synchronize their drive, so communication between driverless cars might be an important improvement. The literature distinguishes a few types of vehicles' communication:

- V2V (vehicle-to-vehicle) vehicles can "talk" to each other.
- V2I (vehicle-to-infrastructure) vehicles can send information to the infrastructure
- I2V (infrastructure-to-vehicle) vehicles can receive information from the infrastructure

Cars equipped with devices enabling communication with other cars and with the infrastructure are named, in short, connected cars. V2V and V2I are jointly named V2X (vehicle-to-everything). V2X communication could be realized, e.g., by dedicated short-range communication (DSRC) or WiFi. DSRC is a short-range wireless communication channel designed for automotive use (Miller and Shaw (2011)). It has many advantages over WiFi, e.g., it is adaptable to bad weather conditions with only small interferences (Goodall (2013)). The approximate range of DSRC is 1000 meters. In 1999, the U.S. Federal Communication Commission (FCC) allocated 75 MHz of spectrum in the 5.9 GHz band for Intelligent Transportation Systems (ITS), FCC (1999). In 2008, the European Telecommunications Standards Institute allocated 30 MHz of spectrum in the 5.9 GHz band for ITS (ETSI, (2008)).

2.2. Traffic models for autonomous and connected vehicles

Traffic modeling is an important aspect of transportation research. Its goal is to develop mathematical tools describing real-world traffic with desired accuracy. There are different approaches to traffic modeling with regard to the level of details: from microscopic level (each car modeled as a separate agent, model describes evolution of car's state, e.g., position and velocity) to macroscopic (traffic described by relations between aggregated values, e.g., speed, flow, density). A comprehensive overview of traffic models can be found in Hoogendoorn and Bovy (2001).

In our research, we develop a microscopic simulation model for autonomous and connected vehicles. The word 'simulation' means in this case that the model is computational, i.e., it should be run on a machine equivalent to Turing Machine or similar models (e.g., Interactive Machine, Goldin (2004), Wegner (1998)) in order to obtain precise evolution of states (positions and speeds) of all cars. Microscopic modeling of (partially) autonomous cars has been developed alongside (partially) autonomous cars, at least since 1960s (Reece and Shafer (1991)). Traffic models including impact of V2X communication started emerging much later, in late 1990s, after such communication became technically feasible. Such traffic models take into account cooperative driving on a highway, changing lane, overtaking (Hu (2012), Jaworski (2013)), synchronizing driving through the crossroad with traffic signals (Goodall (2013), Jaworski (2013)) and without (Vassirani and Ossowski (2011), Chaaban (2014)).

3. Model

3.1. Overall design

The traffic representation designed for the purpose of research on autonomous and connected cars belongs to a group of microscopic traffic models. This means that at every step of simulation, each vehicle is considered as a separate driving unit and vehicle's dynamic parameters, e.g., its position and speed, are updated locally in time.

As far as vehicles' motion is concerned, two major simplifications were applied. Firstly, only a grid of perpendicular lanes is considered. Secondly, turning is simulated as a process that consists of the following stages:

- acquiring the speed that allows turning (in most cases: slowing down)
- getting almost exactly on the position where two lanes cross with each other
- changing the velocity's direction in no time
- · moving towards a new direction

In result, a vehicle can move towards four basic directions (N, E, S, W) only and it always turns at the angle of 90 degrees. Apart from lanes, which are assigned to fixed directions, another considered element of infrastructure is

traffic lights. Vehicles get information (I2V) on the present phase of traffic lights (stop/proceed) and time that is going to elapse before the end of the current phase.

3.2. Concept of BDI agents

The way in which traffic is modeled draws inspiration from the theory of multiagent systems: every vehicle constitutes an individual agent within a simulation.

In accordance with Beliefs-Desires-Intentions agent concept (BDI, Rao and Georgeff (1991)), the main objective of an agent is to satisfy its desires by completing some well-defined goals. In order to plan and execute actions that lead to meeting established goals, an agent needs to gain knowledge about the environment. All information on other agents, obstacles etc. form agent beliefs. In this chapter we explain how BDI abstraction and traits of simulated situation were combined.

3.2.1. Beliefs

We assume that information about the environment (e.g., map, traffic light, positions of obstacles within a defined range) is perfectly accessible to autonomous cars through sensors (e.g., radars, lidars, video cameras) and I2V communication. The simulator instance feeds agents with data on everything that exists or happens within a defined range and does not involve other autonomous cars. Agents acquire information about other autonomous cars within a defined range through V2V communication (Section 3.3.1.). This 2 types of acquiring data are modeled separately in order to mimic the real traffic conditions, in which knowledge about other autonomous vehicles will be acquired mostly by V2V communication (V2I / I2V and sensors may also give some knowledge, but the quality may be lower than V2V). The current design assumes that acquiring data lasts for an insignificantly short period of time.

3.2.2. Desires

Desires represent rules that a vehicle obeys and general requirements it is committed to fulfill (e.g., reaching a destination point, preventing collision). It is convenient to introduce a mechanism that gets necessary information (beliefs) and plans actions of the vehicle so that everything the vehicle does is in accordance with its desires. A desire's property related to its importance is introduced as well. Since some desires are crucial for a vehicle's safety and some just express concern over riding comfort, it is convenient to operate on desires' hierarchies. A will to follow the route and a will to avoid crashes (more important) serve as examples of basic desires.

3.2.3. Intentions and goals

It is assumed that each agent (autonomous car) has a route assigned at the very beginning of its journey. Basing on the route, the agent may define goals, which it intends to complete.

A single goal describes required vehicle's state which consists of all vehicle's dynamic data. As for now, the design allows the state to contain fields with information on:

- position (a pair of coordinates: (x_1, x_2))
- velocity (its value, speed, and direction)
- acceleration (its value and direction).

For example, if a vehicle goes east and should turn right when it arrives at (or close to) the position (x, y), where $x \in [x_1, x_2]$ (the range within which vehicles are allowed to turn at the junction), two goals are set:

Vehicle's state property	Goal no 1	Goal no 2
position	x within the range $[x_1, x_2]$	x within the range $[x_1, x_2]$
velocity speed	within the range $[v_1, v_2]$	Undefined
velocity direction	east	South

Table 1. Exemplary goals for turning right.

We assume that v_1 and v_2 are minimal and maximal velocity, respectively, which are permitted and appropriate for turning. Their values are determined for each intersection.

3.2.4. Actions

A single action is a mechanism that transforms a vehicle's state during the step interval. It may be necessary for a vehicle to meet specific requirements before the execution starts. This serves for emulating real-world situations when a vehicle cannot perform a particular maneuver unless its speed value is included within a given range.

3.3. Simulation step

A simulation process is divided into steps. Execution of each step involves:

- · communication vehicles retrieve information on the environment
- deliberation planning actions which should be executed in the next step
- execution actions planned for the current step are performed, vehicles move forward

Time interval between steps can be flexibly adjusted. If its value is small, then a vehicle's knowledge of the environment's state is updated frequently. It results in a vehicle being able to easily adjust its behavior in dynamic situations. The drawback to consider is that the process of communication and planning that happens too often can be also too time-consuming. On the other hand, if the time interval is long, vehicles have to be more careful when planning their actions (these cannot be changed until the next step). As a consequence, some opportunities to accelerate are missed and driving happens to be not optimal.

3.3.1. Communication

At this stage, the vehicle gains knowledge about the environment within a fixed distance. Information on the infrastructure (including presence and phase of traffic lights) is given by the simulator instance.

Each vehicle also receives messages from the neighboring cars with data regarding their present states (vehicles in front inform on their plans for the current step as well). At the same time it is obligated to broadcast message containing its own parameters and determined actions. In case there is a need to negotiate priorities or plan an alternative routes together, vehicles can get involved in a conversation.

In the current design, an assumption was made that communication between agents is perfectly reliable. Time needed for communication between vehicles is taken into account in an approximate manner. During a step interval only a limited number of messages can be sent or received by a vehicle. The number of exchanged messages within a single conversation is bounded by time too.

3.3.2. Deliberation

Just after an agent's beliefs are updated, a plan for at least the current step has to be drawn up. In order to make right decisions and prepare correct actions, a vehicle makes use of its knowledge base and desires. At the beginning, a neutral action is created. Then it is filtered by desires at all levels.

The process starts with modifications of the original action. Their purpose is to increase speed so that it reaches the desired value, which is set fixed for each vehicle. The modified action is then put aside.

At the next level, a vehicle-agent checks if there are any goals to be accomplished. If so, new goal-oriented actions for the current step are created. Otherwise, the action created by the desire to drive fast is the one to be taken into further consideration.

The last phase makes the plan of actions undergo necessary changes so that the vehicle does not crash into vehicles in the front. To detect and avoid dangerous situations a safety-condition is formulated.

Consider a vehicle moving along the x-axis with velocity $v = [v_x, 0]$. Its maximal deceleration equals a_x . If the vehicle, being at position (x_0, y) , brakes with maximal deceleration, it will stop at position (x_s, y) , where:

$$x_s = x_0 + \frac{v_x^2}{2a_x} \tag{1}$$

If neighboring car within the range and in front of the original vehicle is currently at position (x_0', y) , travels with velocity $v' = [v_x', 0]$, has length d and maximal deceleration a_x' , the following condition should be fulfilled:

$$x_{s}' - x_{s} > d \tag{2}$$

where (x_s', y) is the neighbor's position after it decelerates with a_x' and stops. Equivalently, using formula (1):

$$x_{s}' - x_{s} = x_{0}' + \frac{v_{x}'^{2}}{2a_{x}'} - x_{0} - \frac{v_{x}^{2}}{2a_{x}} > d$$
(3)

Intuitively, if a safety condition is fulfilled, then: if any vehicle in front and within the range of the original one start to brake, there is a guarantee that the original vehicle will manage to slow down rapidly and there will always be a non-zero distance between these two cars. As for now, the role of the "safety desire" is reduced to deciding whether to keep the vehicle's speed being outcome of previous desires (yes, if a resulting situation satisfies (3)) or the speed should be immediately decreased (if the current situation violates (3)).

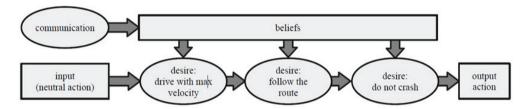


Fig. 1. Deliberation process: how an action is designed.

3.3.3. Execution

As soon as the deliberation process finishes for each of simulated vehicles, all actions planned for the current step are executed one by one. Then, a new vehicle's state is verified for the purpose of crashes detection.

4. Implementation

The simulation, developed solely by authors of this paper, is created within Qt Framework 5.4 (a cross-platform tool based on C++ language and libraries). It allows to model traffic flow for a given set of parameters. The application supports two modes: *The Architect Mode* and *The Simulation Mode*.

4.1. The Architect Mode

Before the simulation process starts, some input data is needed, namely:

- a map with lanes (on each lane vehicles can move in the specified direction only)
- locations of **vehicle sources**: places where vehicles 'appear' on the road and start they travel
- locations of traffic lights
- possible **routes**, which have their beginning in vehicle sources, as well as probabilities assigned to them

Information on these initial conditions has to be provided by a user: either as a plain-text description in JSON format (convenient in case of large-scale maps or data prepared a priori) or entered manually (if just a few intersections are considered). In the second case, a user starts with an empty map and designs the infrastructure by clicking or moving objects around the graphical area. The sidebar menu contains widgets for adjusting numerical values: global constants and local variables. The first kind of values refers to time interval for a simulation step, number of vehicles that start traveling within a step (their number varies with different vehicle sources), size of the map area or width of a single lane. The second group contains sets of values and their probabilities. These are used to determine a single vehicle's size (to model different types of vehicles), route, desired speed, maximal acceleration and deceleration (the last 2 parameters are constant for all vehicles in the current simulator version).

4.2. The Simulation Mode

Within this mode neither parameters nor the map can be changed. While input data is frozen, the simulation process is carried out and visualized. Each simulation step entails generating new vehicles (with routes chosen randomly from the given distribution) and iterating over all active vehicles. Every agent retrieves information on its neighbors' states and infrastructure (outdated or unnecessary messages are filtered out).

Cars that are within the range and in front of the vehicle provide additional information on their plans for the current step – it is possible to determine their future state. Thus, a proper order of processing vehicles is required: if a vehicle A in front has not been processed yet, the vehicle in the back, B, which happened to be considered before A, has to wait until necessary computations involving A are finished.

After deliberation the car decides to undertake some actions. As soon as all cars create their plans, vehicles' states get updated and the next step begins.

Since the range of DSRC is bounded (\sim 1km), limited is also number of vehicles communicating at a given step (in the real traffic and in simulation). Thus, complexity of computations and allocated memory required by a single step are of order O(N), where N is the number of active vehicles (inactive vehicles traveled too far and are no longer on the map).

Throughout the simulation average speed and travel time for a given route are calculated. At each step vehicles' and traffic lights' states are described in textual form and saved in an external file.

5. Discussion of problems

Several simplifications and assumptions introduced as a part of the presented model call for at least a few words of explanation. Some of them mask serious problems that inevitably come with self-driving cars and need to be addressed in the future.

5.1. Distorted or missing messages

In our simulation we assume that exchanging messages is a flawless and stable process. Though, in reality it may suffer from a whole variety of errors. One of them is related to missing packets.

A single message often happens to be too long to be transferred at a stroke from one vehicle to another and for this reason it has to be split into a bunch of smaller message units. What if one of them does not reach its recipient? What if a whole message is missing? Or comes too late? There are a few methods that may help to deal with this risk:

- confirmations a vehicle sends the message at intervals until it gets a confirmation from a recipient
- **retransmission** message units are enumerated so that a vehicle notices when a part of information is missing; if this happens, the recipient sends a request for retransmission
- multiple messages each message that is crucial for safety on the road is sent multiple times by default
- using **other devices** to verify received data a vehicle may use radars, lidars, cameras or other devices to collect data on other vehicles' states exchanged messages are only one of sources of information

None of the mentioned methods constitutes a complete solution to the problem of imperfect communication. A serious drawback of first three of them is increasing time and cost of the process as a whole. Using other devices supports acquiring information on vehicles' states, but does not help with, e.g., negotiations between vehicles.

5.2. Information noise

Another serious problem, which is a minor concern in a simulated world, consists in processing a large amount of data. In a modeled situation, where a group of recipients is unknown and changes dynamically, it is necessary that a vehicle broadcasts messages. Data, which is often needed by only a few vehicles, is sent to every car that happened to be located within the range of a sender. Consequently, a process of filtering incoming messages becomes an important part of self-driving car's software and deserves advanced algorithmic support.

5.3. Cryptographic attacks

It is worth noting that one of significant aspects of communication is ensuring resistance to various hacker attacks. At least, it should be guaranteed that messages come from real vehicles and contain original information. Some of possible solutions make use of distributed authentication systems. Other approaches require existence of trusted central instances that are authorized to certify messages.

As far as present simulations are concerned, this issue remains neglected. In fact, it is a challenge itself, which deserves to be investigated individually and thoroughly.

5.4. Device breakdown

What if a communicator suddenly ceases to work? In a world without traditional cars, a disconnected vehicle shall probably leave the road, if possible, and stop. Then it becomes an obstacle that can be easily noticed by radars of other vehicles. This, however, is not optimal for passengers of this unfortunate vehicle. Perhaps, motion of a vehicle with damaged communicator should be detected and broadcast by elements of infrastructure – then a damaged car could remain a traffic participant without posing a threat to others' safety.

It is worth to emphasize that in the future advanced autonomous cars may have the ability of self-healing (self-repairing) and would be able to repair or replace some broken parts.

5.5. Other independent traffic participants

The simulation does not take into account independent and autonomous traffic participants other than cars of different kinds. Potentially, cyclists or pedestrians could be represented as mobile obstacles encountered on the road. The question arises as to whether they should be given a possibility to communicate with vehicles. Most probably the answer is positive. Especially, if our intention is to get rid of traffic lights - then, replacement solutions are required, e.g., an application for smartphones that allows pedestrians to signal their will to cross the street. Such communication, between vehicles and humans, should be also considered.

6. Conclusions and future work

In the paper we introduced an emerging research area of modeling traffic of autonomous and connected vehicles. We presented our approach based on BDI paradigm: its core assumptions and concepts, implementation, possible extensions and problems relevant to our approach.

Our work is still in progress. The aim is to investigate traffic safety and smoothness depending on various parameters, e.g., configurations of traffic lights, communication time interval length. We also plan to design machine learning methods for developing optimal strategies of driving (for autonomous cars) and traffic control (for traffic management systems). Some additional extensions to be introduced in the future:

- conversations between vehicles or possibility to negotiate vehicles' routes (cars are potentially able to get information on others' goals)
- bidirectional communication with traffic lights (vehicles vote for shorter or longer phases)

- reconstruction of the whole simulation or its clipped part, based on the recorded data
- inclusion in a large-scale traffic simulator, e.g., Traffic Simulation Framework (Gora (2009)).

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