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(54) **TASK-MOTION PLANNING FOR SAFE AND EFFICIENT URBAN DRIVING**

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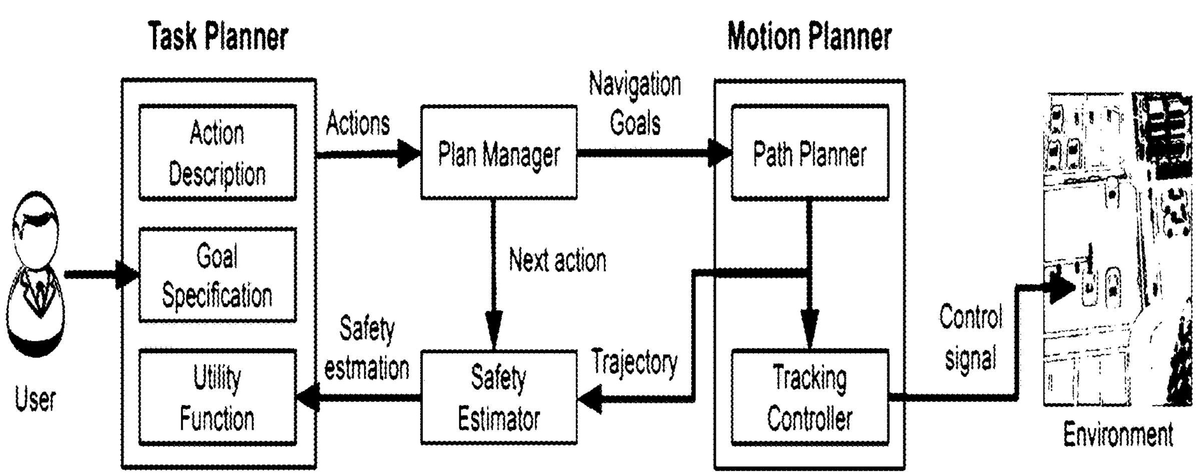
(57) **ABSTRACT**

Autonomous vehicles plan at a task level to compute a sequence of symbolic actions to fulfill service requests, where efficiency is the main concern. The vehicle computes continuous trajectories to perform actions at the motion level, where safety is important. Task-motion planning in autonomous driving faces the problem of maximizing task-level efficiency while ensuring motion-level safety. Task-Motion Planning for Urban Driving (TMPUD) enables the task and motion planners to communicate about the safety level of driving behaviors. The motion planner incrementally advances the vehicle toward a goal with an associated incremental utility, based on at least a safety of motion trajectories. The task planner defines the goal and a sequence of the actions to advance the vehicle toward the goal, dependent an optimization of aggregate prospective utility of the task and the safety of the motion trajectories.

20 Claims, 6 Drawing Sheets



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2022/0058815	A1	2/2022	Xu
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* cited by examiner

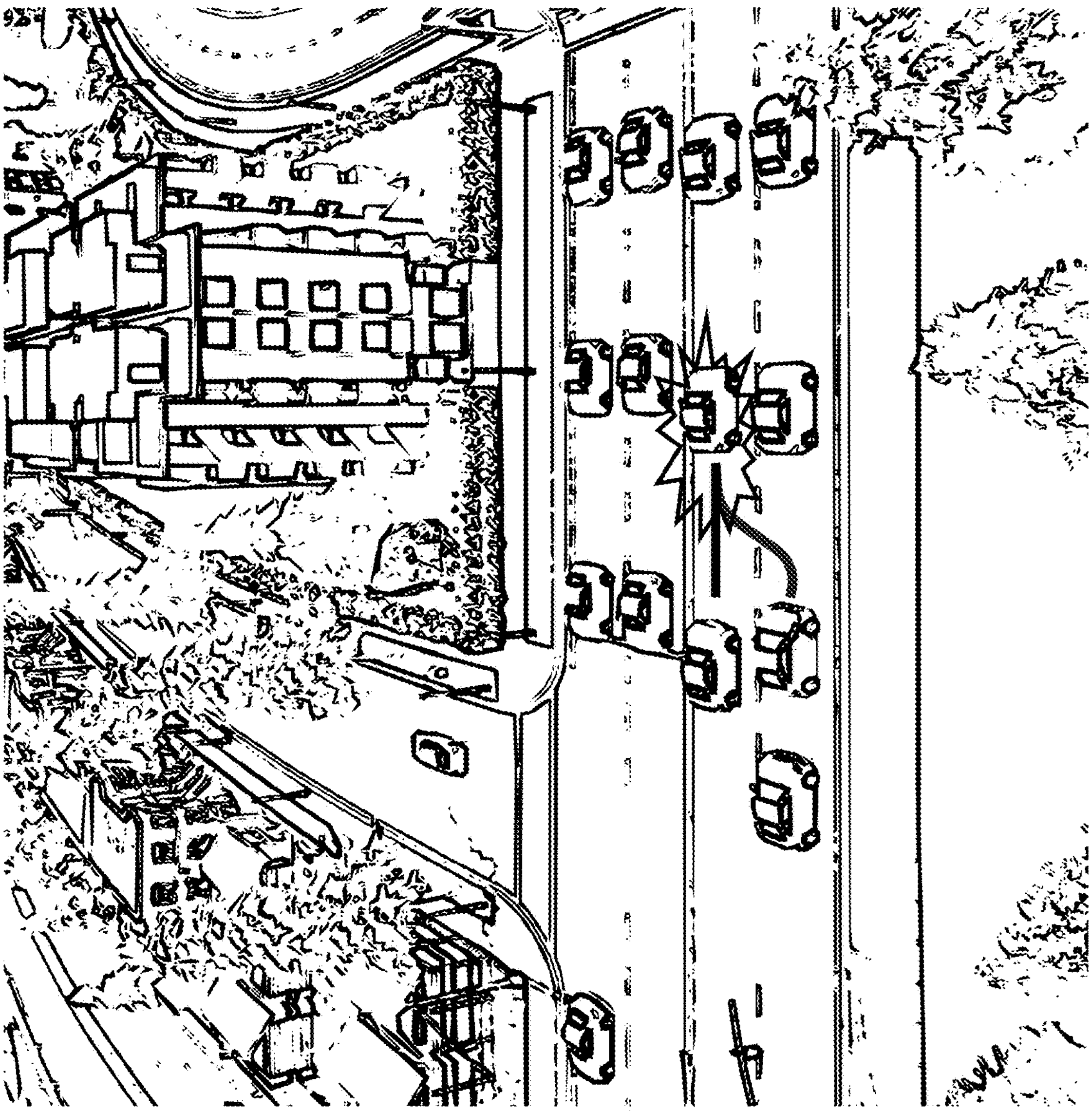


Fig. 1A

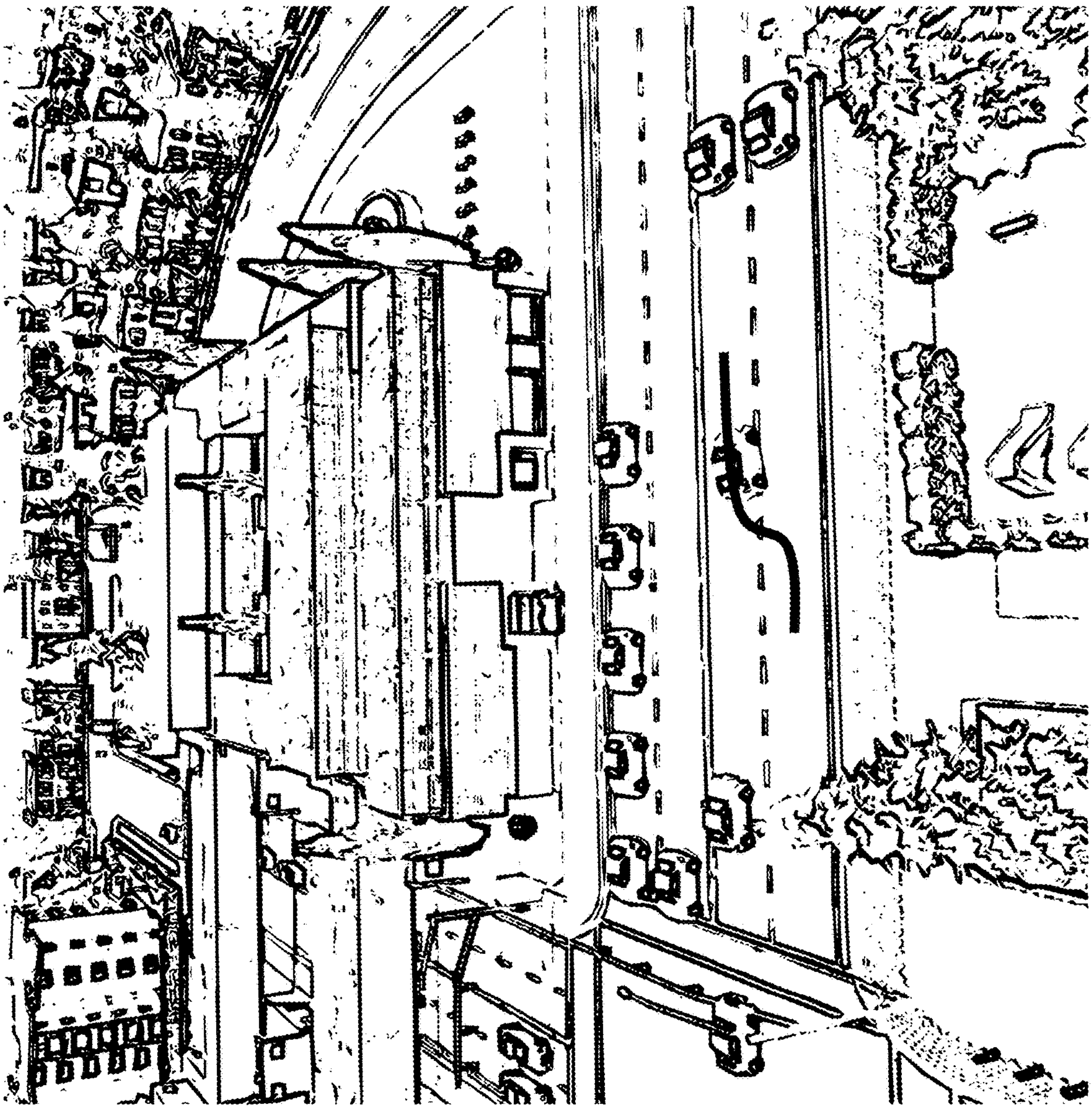
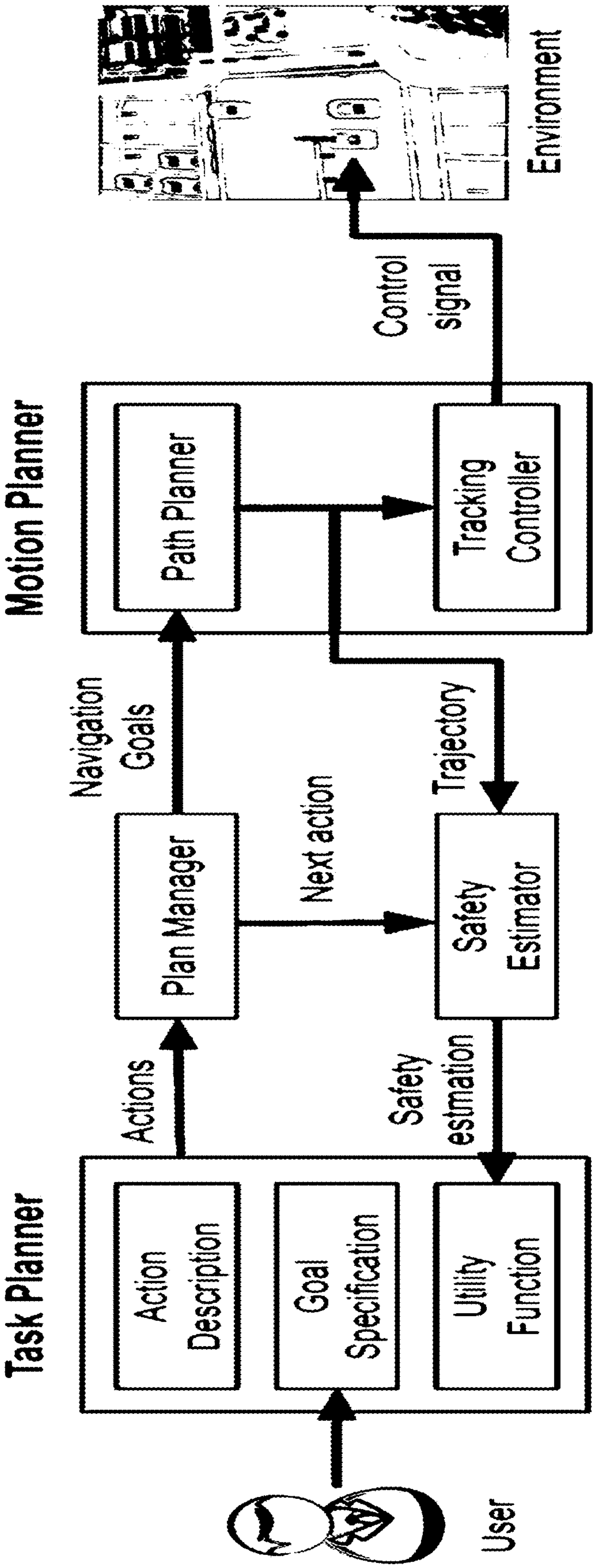


Fig. 1B



Environment
Control signal
Motion Planner
Path Planner
Tracking Controller
Navigation Goals
Trajectory
Plan Manager
Next action
Safety Estimator
Actions
Safety estmation
Task Planner
Action Description
Goal Specification
Utility Function
User

Fig. 2

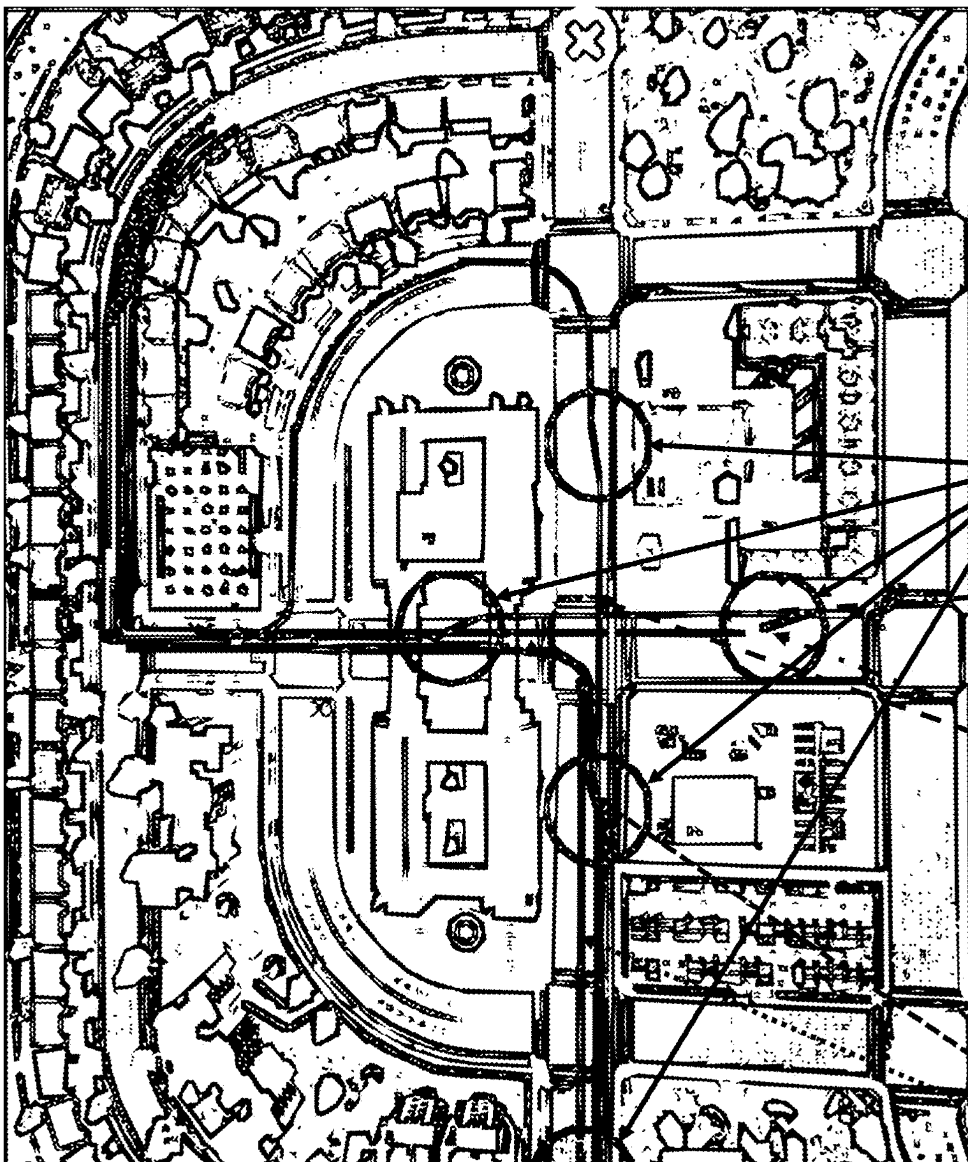

Five Lane Change Areas
Task Plan E
Task Plan C
Task Plan D
Task Plan A
Task Plan B

Fig. 3

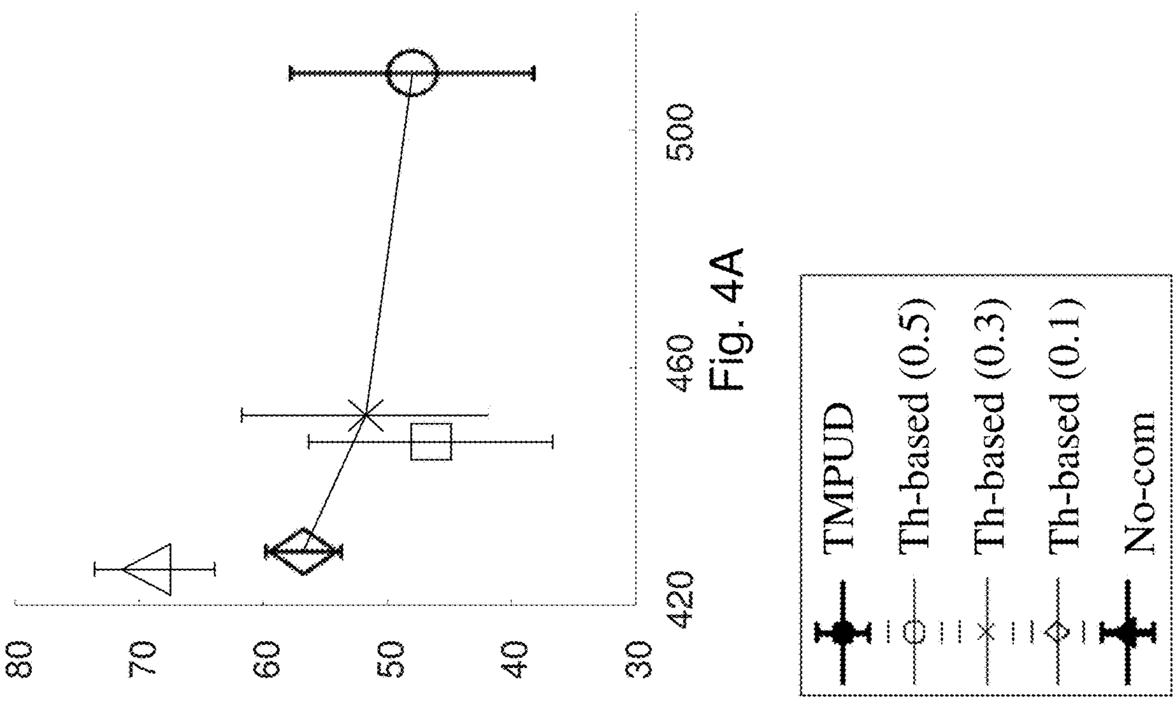

80
70
60
50
40
30
420
460
500
TMPUD
Th-based (0.5)
Th-based (0.3)
Th-based (0.1)
No-com

Fig. 4A

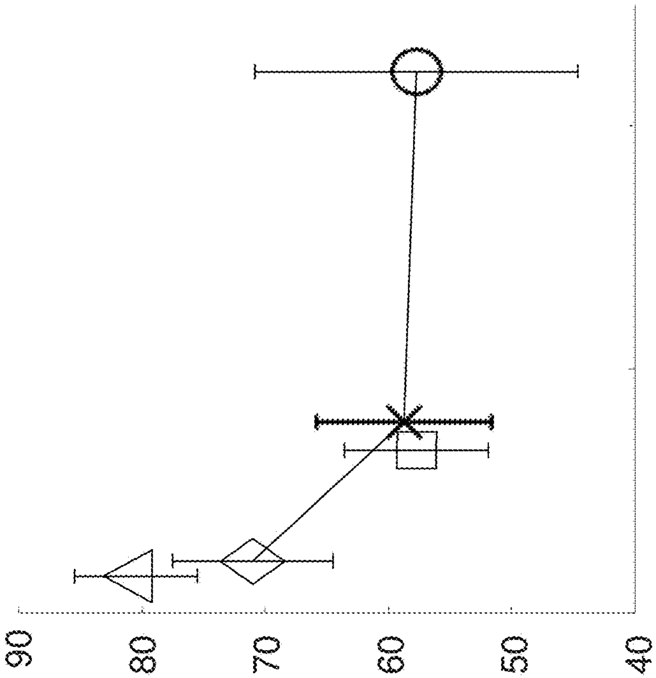

90
80
70
60
50
40
420
460
500

Fig. 4B

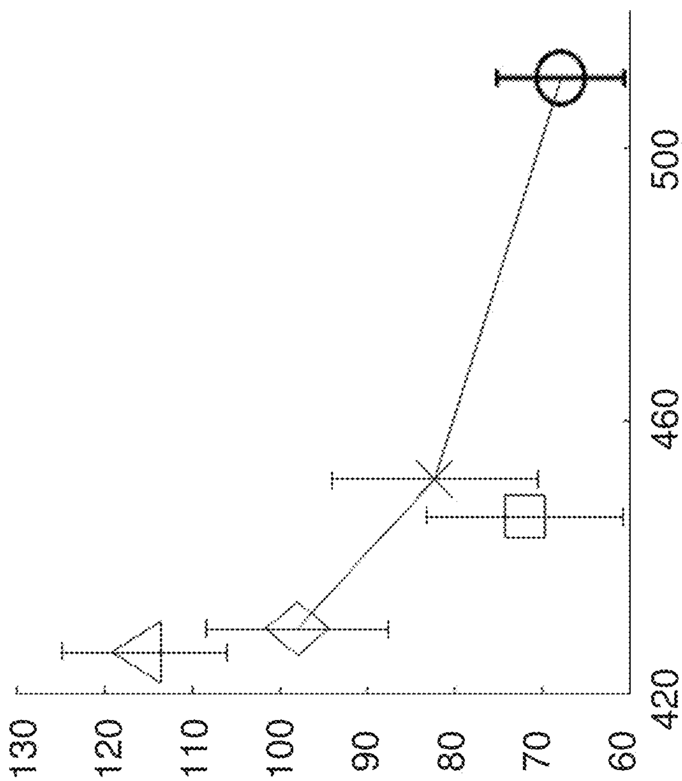

130
120
110
100
90
80
70
60
420
460
500

Fig. 4D

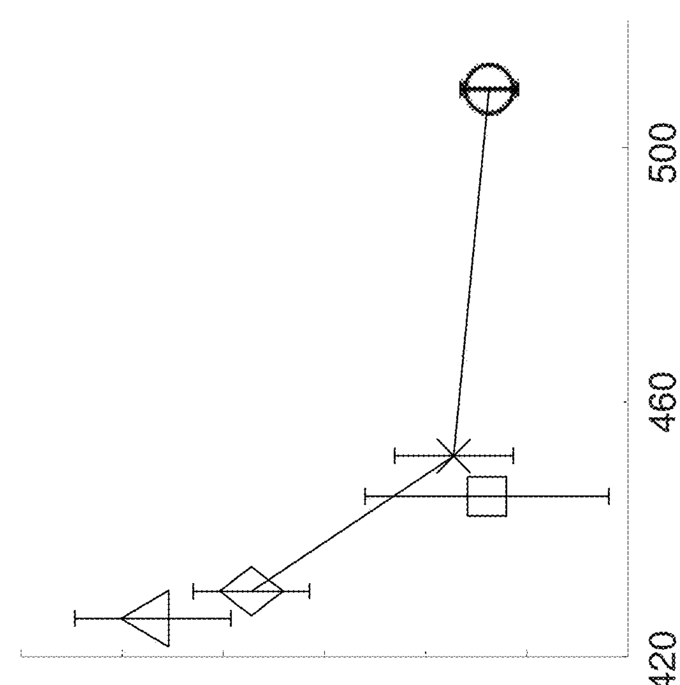

110
100
90
80
70
60
50
420
460
500

Fig. 4C

TASK-MOTION PLANNING FOR SAFE AND EFFICIENT URBAN DRIVING

CROSS REFERENCE TO RELATED APPLICATION

The present application is a non-provisional of, and claims benefit under 35 U.S.C. § 119(e) of, U.S. Provisional Patent Application No. 62/200,431, filed Mar. 5, 2021, the entirety of which is expressly incorporated herein by reference.

FIELD OF THE INVENTION

The present invention relates to the field of autonomous driving systems, and more particularly to a system which enables interaction between task and motion planners.

INCORPORATION BY REFERENCE

Citation or identification of any reference herein, or any section of this application shall not be construed as an admission that such reference is available as prior art. The disclosure of each publication and patent listed or referenced herein are hereby incorporated by reference in their entirety in this application, see 37 C.F.R. § 1.57(c), and shall be treated as if the entirety thereof forms a part of this application. Such references are provided for their disclosure of technologies as may be required to enable practice of the present invention, to provide written description for claim language, to make clear applicant's possession of the invention with respect to the various aggregates, combinations, permutations, and sub-combinations of the respective disclosures or portions thereof (within a particular reference or across multiple references) in conjunction with the combinations, permutations, and sub-combinations of various disclosure provided herein, to demonstrate the non-abstract nature of the technology, and for any other purpose. Except as expressly indicated, the scope of the invention is inclusive, and therefore the disclosure of a technology or teaching within these incorporated materials is intended to encompass that technology or teaching as being an option of, or an addition to, other disclosure of the present invention. Likewise, the combination of incorporated teachings consistent with this disclosure is also encompassed. The citation of references is intended to be part of the disclosure of the invention, and not merely supplementary background information. While cited references may be prior art, the combinations thereof and with the material disclosed herein is not admitted as being prior art.

The incorporation by reference does not extend to teachings which are inconsistent with the invention as expressly described herein as being essential. The incorporated references are rebuttable evidence of a proper interpretation of terms, phrases, and concepts employed herein by persons of ordinary skill in the art. No admission is made that any incorporated reference is analogous art to the issues presented to the inventor, and the selection, combination, and disclosure of these disparate teachings is itself a part of the invention herein disclosed.

BACKGROUND OF THE INVENTION

Autonomous driving technologies have the great potential of reshaping urban mobility in people's daily life [1], [2], [3]. To be deemed useful, autonomous vehicles (hereinafter "vehicles") must be time-efficient in accomplishing service

tasks, which frequently requires symbolic actions such as "Merge left, go straight, turn left, and park right", while at the same time ensuring safety in executing such actions on the road [4], [5], [6].

Generally, autonomous vehicles need to plan at the task level to compute a sequence of symbolic actions toward fulfilling service requests from people. In this process, how the actions are implemented in the real world is out of consideration at the task level. At the same time, vehicles must plan at the motion level to compute continuous trajectories, and desired control signals (e.g., for steering, accelerating, and braking) to implement the symbolic actions. While the task planner hopes that all the symbolic actions can be implemented by the vehicles, there is the safety concern that must be considered at the motion level. For instance, lane-changing behaviors can be dangerous in heavy traffic. FIGS. **1**A and **1**B show two situations for a vehicle that are dangerous and safe, respectively. FIG. **1**A shows a risky situation for the vehicle (blue) to merge left due to the busy traffic. FIG. **1**B shows a safe situation exists for the vehicle to merge left. The goal of TMPUD is to enable the motion level to take symbolic actions from, and communicate safety to the task level toward efficient and safe autonomous driving behaviors.

Although task planning (frequently referred to as behavior planning in autonomous driving [7]) and motion planning have been individually conducted in autonomous driving, there is little research from the literature focusing on the interaction between task and motion levels. There is the critical need of developing algorithms to bridge the gap between task planning and motion planning to help vehicles improve the task-completion efficiency while ensuring the safety of driving behaviors.

The robotics community has studied the integration of task and motion planning, mostly in manipulation domains [8], [9], [10], [11]. In comparison to those domains, autonomous driving algorithms must consider the uncertainty from the ego vehicle, and the surrounding objects (including other vehicles) on the road. The uncertainty must be quantitatively evaluated at the motion level, and taken into consideration for planning at the task level. For instance, when the left lane is busy and missing the next crossing does not introduce much extra distance, the task planner should avoid forcing the vehicle to merge left. Such behaviors are possible, only if the interactions between task and motion levels are enabled.

Motion-Level Planning for Autonomous Driving: Safety is of the most importance at the motion level, and highly relies on the motion-level controllers. Early research in robotics (mostly on manipulation problems) has developed a "safe set" algorithm to avoid unsafe situations in human-robot interactions [14], where it offers a theoretical guarantee of safety. That algorithm has been improved to further account for the uncertainty from the real world [15], where both efficiency and safety were modeled in human-robot interface scenarios. Those methods focused on robot manipulation domains, where it is frequently assumed the acting agent being the only one that makes changes in the world, and hence are not applicable to autonomous driving domains.

Within the autonomous driving context, researchers have developed a series of learning and decision-making methods to enable motion planners to learn safe behaviors [16], [17], [18], [19], [20], [21]. The above-mentioned methods (in robotics and autonomous driving) mainly focus on motion-level behaviors, and do not look into how motion-level behaviors can be sequenced at the task level to accomplish complex driving tasks.

Task-Level Planning for Autonomous Driving: Task planning has been applied to autonomous driving. For instance, one of the earliest works on this topic demonstrated that task planning techniques enable vehicles to complete complex tasks, such as to avoid temporary roadblocks [13]. However, their work did not consider costs of driving behaviors, and hence performs poorly in task-completion efficiency. Similarly, task planners in [22], [23], [24] have no interaction with the motion planner, and safety was not modeled in generating the driving behaviors.

More recent research has enabled vehicles to periodically verify the task sequences and motion trajectories against the actual traffic situation [25]. In case of possible dangers detected at the motion level, re-planning is triggered at the task level. The main limitation of this is that the triggering is deterministic, and highly depends on a safety threshold. The threshold must be set beforehand to ensure safety, which frequently produces over-conservative behaviors, and significantly reduces the task-level efficiency.

Task and Motion Planning: Researchers have integrated task and motion planning in robotics, where the primary domain is robot manipulation [26], [27], [28], [29], [8]. Research on manipulation is mostly concerned with the motion-level feasibility, e.g., in grasping and ungrasping behaviors, and accomplishing high-level tasks, such as stacking objects. Those methods did not consider the uncertainty from other agents (e.g., vehicles on the road). As a result, their systems produce over-optimistic (and hence risky) behaviors, assuming no other agents making changes in the world, and are not applicable to autonomous driving domains.

Further work has surveyed frameworks for autonomous driving [7], including works that plan at both task and motion levels. However, their motion planners do not provide any feedback to the task level, except for infeasible actions.

SUMMARY OF THE INVENTION

The present invention provides a system and method for task and motion planning for urban driving, which is useful for both real-time guidance and autonomous vehicles.

Autonomous vehicles need planning capabilities at two separate levels. On the one hand, at the task level, the vehicle needs to compute a sequence of actions to accomplish human-specific goals (say to buy groceries and add gasoline before going home) using action knowledge provided by domain experts. This so-called task planning problem is traditionally a problem studied in the AI community. On the other hand, the vehicle needs to compute motion trajectories that connect current and goal locations. At the motion level, the vehicle needs to consider its surrounding vehicles to ensure safety. Motion planning is traditionally a robotics problem.

The present technology brings task planning and motion planning together, and applies the integrated system onto autonomous driving scenarios. As a result, an approach, called Task-Motion Planning for Urban Driving (TMPUD), enables efficient task-level behaviors, while ensuring motion-level safety guarantees. See:

Ding, Yan, Xiaohan Zhang, Xingyue Zhan, and Shiqi Zhang. "Task-motion planning for safe and efficient urban driving." In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 2119-2125. IEEE, 2020;

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Woods, Grayson Landis. "Evaluation of Local Kinematic Motion Planning Algorithms for a Truck and Trailer System." PhD diss., 2020.

He, Zichen, Jiawei Wang, and Chunwei Song. "A review of mobile robot motion planning methods: from classical motion planning workflows to reinforcement learning-based architectures." arXiv preprint arXiv:2108.13619 (2021).

An existing task planning (an Answer Set Programming, or ASP), approach, and motion planning algorithms (provided by the CARLA simulator), are used. See,

Lifschitz, Vladimir. Answer set programming. Berlin: Springer, 2019.

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Erdem, Esra, Michael Gelfond, and Nicola Leone. "Applications of answer set programming." AI Magazine 37, no. 3 (2016): 53-68.

Lifschitz, Vladimir. "Answer set planning." In International Conference on Logic Programming and Nonmonotonic Reasoning, pp. 373-374. Springer, Berlin, Heidelberg, 1999.

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Lifschitz, Vladimir. "Answer set programming and plan generation." Artificial Intelligence 138, no. 1-2 (2002): 39-54.

Bonatti, Piero, Francesco Calimeri, Nicola Leone, and Francesco Ricca. "Answer set programming." A 25-year perspective on logic programming (2010): 159-182.

Gebser, Martin, Roland Kaminski, and Torsten Schaub. "Complex optimization in answer set programming." Theory and Practice of Logic Programming 11, no. 4-5 (2011): 821-839.

Niemela, Ilkka, Patrik Simons, and Tommi Syrjanen. "Smodels: a system for answer set programming." arXiv preprint cs/0003033 (2000).

Liu, Guohua, Tomi Janhunen, and Ilkka Niemela. "Answer set programming via mixed integer programming." In Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning. 2012.

Brewka, Gerhard, Thomas Eiter, and Miroslaw Truszczynski. "Answer set programming: An introduction to the special issue." AI Magazine 37, no. 3 (2016): 5-6.

Eiter, Thomas, Giovambattista Ianni, Roman Schindlauer, and Hans Tompits. "A uniform integration of higher-order reasoning and external evaluations in answer-set programming." In IJCAI, vol. 5, pp. 90-96. 2005.

Toni, Francesca, and Marek Sergot. "Argumentation and answer set programming." Logic Programming, Knowledge Representation, and Nonmonotonic Reasoning (2011): 164-180.

US Patent and Patent Application Nos. 20220027737; 20210304066; 20210232915; 20210173831; 20210086370; 20210065027; 20200174765; 20200142732; 20200117575; 20200110835; 20200073739; 20190354911; 20190333164; 20190318411; 20190073426; 20190028370; 20180204122; 20180005123; 20150339355; 20150253768; 20140278683; 20140278682; 20140214582; 20140214581; 20140214580; 20140214487; 20140214474; 20120050787; 20100225954; 20090182786; 11,170,300; 11,165,783; 11,074,103; 11,055,200 11,036,774; 10,977,111; 10,832,141; 10,706,480; 10,705,814; 10,373,268; 10,305,765; 9,925,462; 9,584,535; 9,450,975; 9,135,432; 9,117,201; 9,110,905; 9,100,363; 9,059,960; 9,055,094; 8,990,387; 8,677,486; 8,671,182; 8,601,034; 8,578,002; 8,576,430; 8,474,043; 8,433,790; 8,289,882; 8,272,055; 8,127,353; 7,440,942; 7,219,350; and 7,197,699.

The simulation platform is provided by the autonomous driving community—CARLA, see CARLA.org. It simulates the ego vehicle's behaviors, as long as how the surrounding vehicles respond to the ego vehicle's behaviors. github.com/carla-simulator/carla/blob/dev/LICENSE. See also, US 20220042258; 20210390725; 20210326606; and 20200226377.

Gómez-Hudlamo, Carlos, Javier Del Egido, Luis M. Bergasa, Rafael Barea, Elena López-Guillén, Felipe Arango, Javier Araluce, and Joaquin López. "Train here, drive there: Simulating real-world use cases with fully-autonomous driving architecture in carla simulator." In Workshop of Physical Agents, pp. 44-59. Springer, Cham, 2020.

Niranjan, D. R., and B. C. VinayKarthik. "Deep Learning based Object Detection Model for Autonomous Driving Research using CARLA Simulator." In 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), pp. 1251-1258. IEEE, 2021.

Deschaud, Jean-Emmanuel. "KITTI-CARLA: a KITTI-like dataset generated by CARLA Simulator." arXiv preprint arXiv:2109.00892 (2021).

Stević, Stevan, Momćilo Krunić, Marko Dragojevid, and Nives Kaprocki. "Development and validation of ADAS perception application in ROS environment integrated with CARLA simulator." In 2019 27th Telecommunications Forum (TELFOR), pp. 1-4. IEEE, 2019.

Zhang, Wei, Siyu Fu, Zixu Cao, Zhiyuan Jiang, Shunqing Zhang, and Shugong Xu. "An SDR-in-the-loop Carla simulator for C-V2X-based autonomous driving." In IEEE INFOCOM 2020-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 1270-1271. IEEE, 2020.

TMPUD does not depend on any particular simulation platform, vehicle model, or the selections of task and motion planners. From the simulation perspective, as long as the simulation platform is able to provide how the ego vehicle and environment respond to the ego vehicle's behaviors, they can be used for prototyping and evaluation purposes. TMPUD provides a generic way of computing task-motion plans. CARLA was selected as the evaluation platform because it well supports the simulation of sensors, traffic lights, weathers, and road conditions. However, one can easily implement TMPUD using other popular simulators, such as AirSim (github.com/microsoft/AirSim) and Gazebo (github.com/osrf/gazebo). There are a number of such open-source simulation platforms, and many more that are not open-source.

The technology operates at two different levels; a high level task planning which permits determines goals and intermediate waypoints, for example, as well as low level motion planning which makes short-time scale decisions regarding movement options to achieve the same overall objectives. In general, the high level (long term, prospective, goal oriented) and low level (short term, concurrent, operations-oriented) planning must be both efficient and safe, and these disparate themes are combined using a cost-function. When the motion planner causes a deviation from a nominal task plan, the task planner then re-executes in order to replan the task based on the deviation. One way to consider the task planner and the motion planner is that the former is operative proactively based on predicted states and initial conditions to achieve a plan for a future action, while the motion planner is responsive to initial conditions and real time (sensor) data to plan a current action than as achieved nearly simultaneously with the planning.

Task-Motion Planning for Urban Driving (TMPUD) is thus provided for efficient and safe autonomous urban driving. TMPUD enables the interaction between task and motion planners through enabling the motion-level safety estimation and task-level replanning capabilities.

TMPUD has been evaluated using CARLA, an autonomous driving platform for simulating urban driving scenarios. [12] suggest TMPUD improves both safety and efficiency, in comparison to two baseline methods from the literature [13], [8]. TMPUD supports the interaction between task and motion levels, and aims at improving both safety and efficiency of autonomous driving behaviors. The TMPUD algorithm supports motion-level safety evaluation, and enables the task planner to dynamically adjust high-level plans to account for current road conditions toward accomplishing long-term driving tasks.

Task Planning

A task planning domain is specified by D^t, including a set of states, S, and a set of actions, A. A factored state space is assumed such that each state $s \in S$ is defined by the values of a fixed set of variables; each action $a \in A$ is defined by its preconditions and effects. A utility function maps the state transition to a real number, which takes both cost function Cost(s,a,s') and safety function Safe(s,a,s') into account. Specifically, the cost and safety functions respectively reflect the cost and safety of conducting action a in state s.

Given domain D^t and a task planning problem, a plan $p \in P$ is computed, starting from an initial state $s^{init} \in S$ and finishing in a goal state $s^g \in S$. A plan p consists of a sequence of transitions that can be represented as: $p = \langle s_0, a_0, \ldots, s_{N-1}, a_{N-1}, s_N \rangle$, where $s_0 = s^{init}$, $s^N = s^g$ and P denotes a set of satisfactory plans. Task planner P^t can produce an optimal plan p* among all satisfactory plans, where γ is a constant coefficient and $\gamma > 0$

$$p^* = \underset{p \in P}{\operatorname{argmin}} \sum_{\langle s,a,s' \rangle \in p} \left[\mathrm{Cost}(\langle s, a, s' \rangle) + \frac{\gamma}{1 + e^{Safe(\langle s,a,s' \rangle) - 1}} \right].$$

Motion Planning

A motion planning domain is specified by D^m, where a search is conducted directly in 2D space constrained by the urban road network. Some parts of the space are designated as free space, and the rest are designated as obstacles. The 2D space is represented as a region in Cartesian space such that the position and orientation of the vehicle can be uniquely represented as a pose, denoted by x.

It is noted that the technology is not limited to operation in a 2D space, and rather is also applicable to higher dimensional spaces, e.g., 3D spaces (such as for aerial autonomous vehicles), and ~1D spaces (such as railroad or other constrained path travel).

Given domain D^m, a motion planning problem can be specified by an initial pose x^i and a goal pose x^g. The motion planning problem is solved by a motion planner P^m consisting of path planner and tracking planner into two phases. In the first one, a path planner computes a collision-free trajectory ξ connecting pose x^i and pose x^g taking into account any motion constraints on the part of the vehicle with minimal trajectory length. In the second one, a tracking controller computes desired control signals to drive the vehicle to follow the computed trajectory. Due to the fundamental difference between representations at task and motion levels, in line with past research [26], [29], [8], [11], a state mapping function, f:X=f(s), is used to map the symbolic state s into a set of feasible poses X in continuous space, for motion planner to sample from. Availability of at least one pose x∈X is assumed in each state s, such that the vehicle is in the free space of D^m. If it is not the case, the state s is declared infeasible.

Safety Estimation

Safety estimation aims at computing the safety level, Safe(⟨s,a,s'⟩), of the motion-level implementation of a symbolic action ⟨s,a,s'⟩. The goal of computing the safety value is to enable the task planner to incorporate the road condition into the process of sequencing high-level actions toward accomplishing complex driving tasks.

To perform symbolic action ⟨s,a,s'⟩, a motion planner is used to compute a sequence of continuous control signals, i.e., acceleration δ∈Δ and steering angle θ∈Θ, to drive the vehicle following the planned trajectory, while ensuring no collision on the road. Sets Δ and Θ denote the operation specification of the controller, which generally depends on the adopted motion planner and the ego vehicle itself. Let $U_s(t)$ (mathematically $U_s(t) \subset \Delta\times\Theta$) specify a safe control set at time t, in which all elements, denoted by u(t)=⟨δ,θ⟩, are safe for an ego vehicle to perform at time t. Intuitively, the size of safe control set U_s reflects the safety level. For instance, when $|U_s|$ is very small, meaning that very few control signals are safe, the vehicle can only be operated in very particular ways, indicating the safety level in general is low. Accordingly, the probability of elements sampled from set Δ×Θ being located in the safe set U_s is to represent the safety value of action ⟨s,a,s'⟩.

Safety Estimation Algorithm

Algorithm 1 summarizes the procedure of the safety estimation algorithm. The input includes symbolic action ⟨s,a,s'⟩, stating mapping function f, motion planner P^m consisting of path planner and tracking controller, and the controller's operation specification sets Δ and Θ. The output is the estimated safety value Safe(⟨s,a,s'⟩)∈[0.0,1.0].

In algorithm 1, lines 1-3 aim to obtain the short-period trajectories of the ego and surrounding vehicles, where V_i,i∈[1, . . . , N] is the ith vehicle within the ego vehicle's sensing range. More specifically, a first sample of a pair of feasible initial and goal poses for the symbolic actions using the state mapping function (Line 1). Taking these two poses as input, the motion planner then computes a continuous trajectory for the ego vehicle for a short period of time $[t_1,t_2]$ (Line 2), where t_1 is the current time, and $t_2=t_2+T$ indicates the time horizon of the ego vehicle. Surrounding vehicles' trajectories are predicted, assuming their linear and angular speeds being stationary (Line 3), though there are more advanced methods [30], [31].

Lines 4-8 of algorithm 1 present a control loop that computes the safety estimation between the ego vehicle and the surrounding vehicles V_i, where i∈[1, . . . , N], given that the ego vehicle is performing action ⟨s,a,s'⟩ at the motion level. A safe control set $U_i^s(t)$ is computed, similar to [19], that includes all safe control signals with regard to vehicle V_i at time t (Line 5). Parameter ω controls the sampling interval.

In Line 6 of algorithm 1, M elements are randomly sampled from the set Δ×Θ, and compute probability $o_i(t)$ of the sampled elements falling in set $U_i^s(t)$. A list of values of safety estimation $\{o_i(t)\}$ is converted into a single value o^*_i using eqn. 1, where max and mean are two functions to calculate the maximum and mean value of a list, respectively (Line 7). Although all surrounding vehicles can potentially introduce risks to the ego vehicle, the ego vehicle is assumed to only consider the most dangerous vehicle. Accordingly, Line 9 is used for selecting the minimum value, o^*_i,i∈[1, . . . , N], as the overall safety value:

$$o_i^* = \frac{\max_{t\in T}\{o_i(t)\} + mean_{t\in\mathcal{T}}\{o_i(t)\}}{2} \tag{1}$$

$$\text{Where } \mathcal{T} = t_1 + \omega\times i,\ 0 \le i \le \frac{(t_2 - t_2)}{\omega}$$

Algorithm 1 Safety Estimation

Input: Symbolic action ⟨s,a,s'⟩, state mapping function f, motion planner P^m, control operation sets Δ and Θ

1: Sample initial and goal poses, x←f(s) and x'←f(s'), given action ⟨(s,a,s'⟩, and f.
2: Compute a collision-free trajectory, ξ^E, using P^m, where $\xi^E(t_1)$=x,$\xi(t_2)$=x'; and $[t_1,t_2]$ is the horizon
3: Predict trajectory ξ_i^s for the ith surrounding vehicle, where i∈[1, . . . , N], and $[t_1,t_2]$ is the horizon
4: while for each vehicle V_i do
5: Compute safe control set $U_i^s(t)$ between the ego vehicle and vehicle V_i at time t∈$[t_1,t_2]$, where $U_i^s(t) \in \Delta\times\Theta$ and

$$t = t_1 + \omega\times i,\ i \le \frac{(t_2 - t_2)}{\omega}$$

6: Sample M elements ⟨δ,θ⟩ randomly from set Δ×Θ and compute the probability $o_i(t)$ of the elements falling in set $U_i^s(t)$
7: Convert a list of estimated safety values, $\{o_i(t)\}$, into a scalar value o^*_i using Eqn. 1
8: end while
9: return min{o^*_i, i=1, . . . , N}

TMPUD

The motion planner P^m computes both costs (trajectory lengths) and safety values of the ego vehicle's navigation actions.

s^{init} is used to represent the initial state of the ego vehicle, and the goal (service request from people) is specified using s^g. The task planner P^t computes a sequence of symbolic actions, and it requires two functions that are initialized and updated within the algorithm, including cost function Cost, and safety estimation function Safe. Motion planner P^m is used for computing motion trajectories, and generating control signals to move the ego vehicle. The state mapping function f is used for mapping symbolic states to 2D coordinates in continuous spaces.

The TMPUD Algorithm

Algorithm 2 summarizes the procedure of TMPUD. It starts by initializing the cost and safety estimation functions (Lines 1 and 2 of algorithm 2). Cost function Cost is initialized using the A* algorithm provided by CARLA, as shown in Line 1 of algorithm 2. In Line 2 of algorithm 2, TMPUD optimistically initializes the safety estimation function by setting 1.0 to all actions, indicating all task-level actions are completely safe. After that, an optimal task plan, $p^* = \langle s^{init}, a_0, s_1, \ldots, s^g \rangle$ is computed in Line 3 of algorithm 2. The head and tail elements of the plan, s^{init} and s^g, correspond to the initial and goal poses respectively.

Lines 4-19 of algorithm 2 form TMPUD's main control loop that enables the interaction between task and motion planners. The loop's termination condition is the task-level plan being empty, i.e., the goal has been achieved (Line 4 of algorithm 2). Specifically, TMPUD estimates the safety level, μ, of action $\langle s,a,s' \rangle$ (Line 5 of algorithm 2). Functions Safe and Cost are updated using μ and A* search in Line 6 of algorithm 2. Then a new optimal plan p' is computed in Line 7 of algorithm 2. Lines 8-18 of algorithm 2 is for plan monitoring and action execution. If the task planner suggests the same plan (Line 8 of algorithm 2), the vehicle will continue to execute action a at the motion level. The goal state is sampled from state mapping function in Line 9 of algorithm 2. Lines 10-14 of algorithm 2 is a loop to execute the action. Specifically, the motion planner will compute and execute a desired control signal $\langle \delta,\theta \rangle$ repeatedly until the vehicle reaches the goal pose (Line 10 of algorithm 2). The vehicle's current pose x will be updated after each execution (Line 13 of algorithm 2). After completing the operation, the tuple $\langle s,a \rangle$ will be removed from the plan p (Line 15 of algorithm 2). On the contrary, if the task planner suggests a new plan p' different from the plan p, the currently optimal p' will replace the non-optimal plan p (Line 17 of algorithm 2).

Algorithm 2 TMPUD algorithm

Input: Initial state s^i, goal specification s^g, task planner P^t, state mapping function f, motion planner P^m, and safety estimator (Algorithm 1)

1: Initialize cost function Cost with sampled poses $x \in f(s)$: $Cost(\langle s,a,s' \rangle) \leftarrow A^*(x,x')$
2: Initialize safety estimation $Safe(s,a,s') \leftarrow 1.0$
3: Compute an optimal task plan p using Cost and Safe functions:

$$p \leftarrow P^t(s^{init}, s^g, \text{Cost}, \text{Safe}), \text{ where } p = \langle s^{init} \rightarrow a_0, s_1, a_1, \ldots, s^g \rangle$$

4: while Plan p is not empty do
5: Extract the first action of p'(s,a,s') and compute safety value p using Algorithm 1
6: Update Safe function: $Safe(\langle \in a, s' \rangle) \leftarrow \mu$ and Cost function:

$$\text{Cost}(\langle s,a,s' \rangle) \leftarrow A^*(x,x')$$

7: Generate a new plan: $p' \leftarrow P^t(s, s^g, \text{Cost}, \text{Safe})$
8: if p'==p then
9: $x' \leftarrow f(s')$
10: while x!=x' do
11: Call motion planner $\langle \delta,\theta \rangle \leftarrow P^m(x,x')$
12: Execute the control signal $\langle \delta,\theta \rangle$
13: Update the vehicle's current pose x
14: end while
15: Remove the tuple $\langle s, a \rangle$ from plan p
16: else
17: Update current plan $p \leftarrow p'$
18: end if
19: end while

Task Planner

The task planner P^t is implemented using Answer Set Programming (ASP), which is a popular declarative language for knowledge representation and reasoning, and ASP has been used for task planning [32], [33], [11], [34]. For example, predicate leftof(La**1**,La**2**) can be used to specify lane La**1** being on the left of lane La**2**. Five driving actions are modelled, including mergeleft, mergeright, forward, turnleft, and turnright. For instance, action mergeright can be used to help the vehicle merge to the right lane, where constraints, such as "changeright" is allowed only if there exists a lane on the right, have been modeled as well.

Motion Planner

At the motion level, path planner firstly generates a desired continuous trajectory with the minimal traveling distance using A* search. The trajectory includes a set of waypoints (each in the form of a pair of x-y coordinate and orientation), and the trajectory is delivered to the tracking controller, along with the vehicle's current pose and speed. The controller uses a proportional-integral-derivative (PID) controller [35] to generate control signals, e.g., for steering, throttle, and brake. PID controller is very popular due to its simplicity, flexibility, and robustness.

CARLA, an open-source 3D urban driving simulator [12] was been developed to support development, training, and validation of autonomous driving systems. Compared to other simulation platforms, e.g., [36], [37], see, U.S. Pat. Nos. 11,150,655; 11,030,476; 10,997,467; 10,596,339; 9,662,068; 11,150,658; 10,588,033; 10,425,954; 20210394788; 20210311504; 20210278854; 20210271253; 20210133502; 20210117730; 20190004518; 20220058815; 20220057804; 20220055215; 20210287556; 20210247781; 20210088337; 20200310444; 20200293053; 20200293052; 20200293051; 20190053074; and 20180288774, CARLA provides open digital assets (urban layouts, buildings, vehicles) that were created for this purpose and can be used freely.

See also:

Bondi, Elizabeth, Debadeepta Dey, Ashish Kapoor, Jim Piavis, Shital Shah, Fei Fang, Bistra Dilkina et al. "Airsim-w: A simulation environment for wildlife conservation with uavs." In Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, pp. 1-12. 2018.

Shah, Shital, Debadeepta Dey, Chris Lovett, and Ashish Kapoor. "Airsim: High-fidelity visual and physical simulation for autonomous vehicles." In Field and service robotics, pp. 621-635. Springer, Cham, 2018.

Nguyen, Justin, Peter K. Nguyen, and Mujahid Abdulrahim. "Development of an Unmanned Traffic Management Simulation with Robot Operating System and Gazebo." In AIAA SCITECH 2022 Forum, p. 1918. 2022.

Mehrooz, Golizheh, Emad Ebeid, and Peter Schneider-Kamp. "System design of an open-source cloud-based framework for internet of drones application." In 2019 22nd Euromicro Conference on Digital System Design (DSD), pp. 572-579. IEEE, 2019.
Zhu, Donglin, Guanghui Xu, Xiaoting Wang, Xiaogang Liu, and Dewei Tian. "PairCon-SLAM: Distributed, Online, and Real-Time RGBD-SLAM in Large Scenarios." IEEE Transactions on Instrumentation and Measurement 70 (2021): 1-14.
Nikolenko, Sergey I. "Synthetic Simulated Environments." In Synthetic Data for Deep Learning, pp. 195-215. Springer, Cham, 2021.
de Figueiredo, Rui Pimentel, Jonas le Fevre Sejersen, Jakob Grimm Hansen, Martim Brandao, and Erdal Kayacan. "Real-Time Volumetric-Semantic Exploration and Mapping: An Uncertainty-Aware Approach." In 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 9064-9070. IEEE, 2021.
Yoon, Sugjoon, Dongcho Shin, Younghoon Choi, and Kyungtae Park. "Development of a flexible and expandable UTM simulator based on open sources and platforms." Aerospace 8, no. 5 (2021): 133.

The CARLA software provides two functionalities: First, it enables an ego vehicle to evaluate the safety level based on its surrounding vehicles' locations and speeds. Second, it computes task-level plans (a sequence of symbolic actions), and motion-level plans (a trajectories in continuous space) at the same time.

An autonomous vehicle (AV) (e.g., a driverless car, a driverless auto, a self-driving car, a robotic car, etc.) is a vehicle that is capable of sensing an environment of the vehicle and traveling (e.g., navigating, moving, etc.) in the environment without human input. An AV uses a variety of techniques to detect the environment of the AV, such as radar, laser light, lidar, Global Positioning System (GPS), odometry, and/or computer vision. In some instances, an AV uses a control system to interpret information received from one or more sensors, to identify a route for traveling, to identify an obstacle in a route, and to identify relevant traffic signs associated with a route.

The AV includes a processor, which may be local to the AV, remote from the AV at a data center, for example, or distributed through a variety of predetermined or ad hoc computing resources. Often, it is useful to implement artificial intelligence and/or machine learning to help manage the extremely high dimensionality of the sensor dataset, rule base, and control options. The processor may include reduced instruction set computing (RISC) processors, complex instruction set processors (CISC), single instruction-multiple data (SIMD) processors or other parallel processing systems, artificial neural network (ANN) processors or implementations, field programmable gate arrays (FPGA), application-specific integrated circuits (ASIC) and the like, and typically will include multiple processors, with some dedicated to particular tasks.

An autonomous vehicle (AV) map of a geographic location may be used for determining nominal driving paths on lanes of roadways (e.g., roadway segments) in the map on which an AV may operate (e.g., route, travel, or perform one or more autonomous operations). For example, a nominal driving path including one or more lanes on one or more roadway segments is determined by generating a center line through lane boundaries of a lane. However, a nominal driving path may not describe a proper driving path through lanes on roadway segments over which an AV can travel. For example, nominal driving paths may include inconsistencies associated with the lane boundaries of the roadway. As an example, a centerline of lane boundaries may provide inaccuracies for AV travel, based on different markings from a first lane to a second lane in a roadway where the width of the lane boundaries are determined. Additionally or alternatively, an AV of a first size may not operate on a nominal driving path, the same as an AV of a second size on the same nominal path. For example, a large sized AV may be limited (e.g., constrained) in movement as compared to a smaller sized AV when traversing a nominal driving path based on the lane boundaries in the roadway of the AV map. Additionally or alternatively, a nominal driving path may be inefficiently determined from aspects of a lane polygon that requires additional storage of points on the polygon and/or additional computations. In this way, a nominal driving path may be less complete and/or result in less efficient processing for operating and/or routing the AV. In addition, a map may be generated that provides an AV fewer operating options and/or driving options, may not account for the proper structure of lanes, and/or may implement additional processing functions to modify or augment the AV map for lanes with incomplete or incorrect physical markings. Therefore, while maps are useful, and permit geographic reference of structures and events, they typically cannot be relied upon for safe traverse during operation of the AV, and sensor data and real-time processing is required for safety and reliability. Further, the limitations on the data available before a task is begun, or before a portion of a task is implemented, impose limits on task planning.

Therefore, an AV should have processing capability for both safe motion planning and task planning available during operation.

A map generation system may contain or receive map data associated with a map of a geographic location, wherein the map data is associated with a roadway or traverse passage in the geographic location. The map generation system determines a general motion path including one or more trajectories for an AV, and the map data may be acquired by various means, and preferably based on one or more traversals of the path by one or more vehicles. The map generation system may generate driving path information based on one or more trajectory points in the one or more trajectories of the driving path. In this way, the map generation system provides and/or generates the driving path data associated with the driving path to an AV for controlling travel of the AV.

A vehicle computing system of an AV may receive driving path data associated with a desired path, including one or more trajectories (or ranges or limits on the available trajectories) that an AV can traverse. For example, the actual travel path and trajectory may be dependent on vehicle speed, traffic, obstacles or hazards, uncontrolled excursions from the desired path (e.g., skids), weather, and other factors.

The AV will therefore typically plan a route in advance of travel, and then make decisions during travel for particular path options dependent on real-time calculations. In this case, a real time calculation is meant to encompass calculations that occur between receipt of sensor data and when the AV must respond to the sensor data to avoid adverse effect. For example, an adaptive suspension may require millisecond scale response times, while a path planning system responsive to a posted traffic signal observed by a camera may have seconds of planning time.

The AV computing system can determine at least one feature of the environment or roadway in the intended (or avoided) path based on the map data, non-real time data (such as historical or old traffic data) and real-time data. In some cases, the vehicle computing system can determine a lateral constraint associated with lateral movement of the AV based on the driving path data associated with the trajectory. Accordingly, the map enables the vehicle computing system to generate and/or traverse a route in a more efficient manner with less processing delays and/or routing for the AV to be performed by the vehicle processing system (e.g., completely by the vehicle processing system).

The map generation system and/or the AV may include one or more devices capable of receiving, storing, and/or providing map data associated with a map of a geographic location (e.g., a country, a state, a city, a portion of a city, a township, a portion of a township, etc.). For example, AV maps are used for routing an AV on a roadway specified in the AV maps. The map data may include data associated with a road (e.g., an identity and/or a location of a roadway of a road, an identity and/or location of a segment of a road, etc.), data associated with features of a road, such as an object in proximity to a road (e.g., a building, a lamppost, a crosswalk, a curb of the road, etc.), data associated with a lane of a roadway (e.g., the location and/or direction of a travel lane, a parking lane, a turning lane, a bicycle lane, etc.), data associated with traffic control of a road (e.g., the location of and/or instructions associated with lane markings, traffic signs, traffic lights, etc.), and/or the like. A map of a geographic location may include one or more routes that include one or more roadways. Map data associated with a map of the geographic location may associate each roadway of the one or more roadways with an indication of whether an AV can travel on that roadway. Features of a road may be based on data collected by and/or received from one or more sensors located on an AV as the AV travels on one or more roads in a geographic location.

The map may include dynamic information, such as traffic light timing, diurnal/weekly/monthly/annual traffic density patterns and changes, correlations between patterns at different locations, etc. Further, to the extent that the map is available for use by a human occupant of the AV, the map may also include points of interest, sponsored points of interest (location-based advertising), promotions, and the like. Further, the map may include locations of electric vehicle (EV) charging stations, to allow planning energy availability and replenishment, in addition to endpoint route.

A road refers to a paved or otherwise improved path between two places that allows for travel by a vehicle (e.g., an AV). Additionally or alternatively, a road includes a roadway and a sidewalk in proximity to (e.g., adjacent, near, next to, touching, etc.) the roadway. A roadway may include a portion of road on which a vehicle is intended to travel and is not restricted by a physical barrier or by separation so that the vehicle is able to travel laterally. Additionally or alternatively, a roadway includes one or more lanes, such as a travel lane (e.g., a lane upon which a vehicle travels, a traffic lane, etc.), a parking lane (e.g., a lane in which a vehicle parks), a bicycle lane (e.g., a lane in which a bicycle travels), a turning lane (e.g., a lane in which a vehicle turns from), and/or the like. A roadway may be connected to another roadway, for example a lane of a roadway may be connected to another lane of the roadway and/or a lane of the roadway may be connected to a lane of another roadway.

Note that the present technology is not limited to on-road automobiles, and rather may be used for off-road, unmanned autonomous vehicles (UAV), pedestrians, bicycles, mopeds, motorcycles, snowmobiles, and other types of vehicles or travel situations. The present technology in general seeks to optimize the task planning with the motion planning in a safe and efficient manner. Note that safety is often a statistical consideration, and what is managed is the margin of safety or predicted margin of safety, since other than in extreme cases, operation in a designated unsafe manner is undesirable. On the other hand, in certain sports or emergencies, operation outside of safe ranges is desired, and this can also be accommodated within the paradigm. Likewise, efficiency is typically desired, but the metric may be designed based on various cost functions. Thus, where time is of the essence, a high weighting of time maty lead to an optimal path which would otherwise be considered inefficient or unsafe, or both. More generally, by combining the various considerations of efficiency and safety into a combined determination, hard constraints are avoided, and therefore more options are available during motion to achieve an optimal result.

A map generation system may include one or more devices capable of receiving map data, determining a driving path for an AV including one or more trajectories in a lane of the roadway based on one or more traversals of the roadway by one or more vehicles, generating driving path information based on one or more trajectory points in the one or more trajectories of the driving path in the roadway, and/or providing driving path data associated with the driving path for controlling the AV. For example, the map generation system can include one or more computing systems including one or more processors (e.g., one or more servers, etc.).

AVs may include one or more devices capable of receiving driving path data and determining a route in a lane including a driving path based on the driving path data. The AV may include one or more devices capable of controlling travel, operation, and/or routing of the AV based on the driving path data. For example, the one or more devices may control travel and one or more functionalities associated with the fully autonomous mode of the AV in a lane on the driving path, based on the driving path information including feature information associated with the driving path, for example, by controlling the one or more devices (e.g., a device that controls acceleration, a device that controls steering, a device that controls braking, etc.) of AV based on sensor data, position data, and/or map data associated with determining the features in the lane. The AV may include one or more devices capable of receiving map data, determining a route in a lane that includes the driving path for an AV, including one or more trajectories in a roadway based on one or more traversals of the roadway by one or more vehicles, generating driving path information based on one or more trajectory points in the one or more trajectories of the driving path in the roadway, and/or providing driving path data associated with the driving path for controlling the AV. For example, AV can include one or more computing systems including one or more processors (e.g., one or more servers, etc.).

The map generation system and/or AV may include one or more devices capable of receiving, storing, and/or providing map data (e.g., map data, AV map data, coverage map data, hybrid map data, submap data, etc.) associated with a map (e.g., a map, a submap, an AV map, a coverage map, a hybrid map, etc.) of a geographic location (e.g., a country, a state, a city, a portion of a city, a township, a portion of a township, etc.). For example, maps are used for routing AV on a roadway specified in the map.

The network may include one or more wired and/or wireless networks. For example, the network may include a cellular network (e.g., a long-term evolution (LTE) network, a third generation (3G) network, a fourth generation (4G) network, a fifth generation (5G) network, a sixth generation

(6G) network, a WiFi network (e.g., within IEEE-802.11 series of standards, e.g., WiFi 5, WiFi 6, WiFi 6E, WiFi 7), a low earth orbiting satellite network, Starlink, WiMax, etc.), a local area network (LAN), a wide area network (WAN), a metropolitan area network (MAN), an ad hoc network, the Internet, a fiber optic-based network, a cloud computing network, and/or the like, and/or a combination of these or other types of networks.

The AV computing system may include vehicle command system, perception system, prediction system, task planning system, and motion planning system that cooperate to perceive a surrounding environment of AV, determine a motion plan and control the motion (e.g., the travel vector and parameters) of AV accordingly.

The AV computing system may be is connected to or include a positioning system. The positioning system may determine a position (e.g., a current position, a past position, etc.) of AV, and typically includes a geographic positioning system (GPS) and/or inertial guidance system. The positioning system may determine a position of AV based on an inertial sensor, a satellite positioning system, triangulation based on network components (e.g., network access points, cellular towers, Wi-Fi access points, etc.), and/or proximity to network components, and/or the like.

The AV computing system may receive sensor data from one or more sensors that are coupled to or otherwise included in AV. For example, one or more sensors may include a Light Detection and Ranging (LIDAR) system, a Radio Detection and Ranging (RADAR) system, one or more cameras (e.g., visible spectrum cameras, infrared cameras, etc.), and/or the like. The sensor data may include data that describes a location of objects within the surrounding environment of the AV. One or more sensors may collect sensor data that includes data that describes a location (e.g., in three-dimensional space relative to the AV) of points that correspond to objects within the surrounding environment of AV.

The sensor data may include a location (e.g., a location in three-dimensional space relative to the LIDAR system) of a number of points (e.g., a point cloud) that correspond to objects that have reflected a ranging laser. The LIDAR system may measure distances by measuring a Time of Flight (TOF) that a short laser pulse takes to travel from a sensor of the LIDAR system to an object and back, and the LIDAR system calculates the distance of the object to the LIDAR system based on the known speed of light. Map data may include LIDAR point cloud maps associated with a geographic location (e.g., a location in three-dimensional space relative to the LIDAR system of a mapping vehicle) of a number of points (e.g., a point cloud) that correspond to objects that have reflected a ranging laser of one or more mapping vehicles at the geographic location. As an example, a map can include a LIDAR point cloud layer that represents objects and distances between objects in the geographic location of the map.

The sensor data may include a location (e.g., a location in three-dimensional space relative to the RADAR system) of a number of points that correspond to objects that have reflected a ranging radio wave. Radio waves (e.g., pulsed radio waves or continuous radio waves) transmitted by the RADAR system can reflect off an object and return to a receiver of the RADAR system. The RADAR system can then determine information about the object's location and/or speed. The RADAR system may provide information about the location and/or the speed of an object relative to the RADAR system based on the radio waves. Multipath exploitation RADAR may be used to detect non-line of sight features.

Image processing techniques (e.g., range imaging techniques, such as, for example, structure from motion, structured light, stereo triangulation, etc.) can be performed by the system to identify a location (e.g., in three-dimensional space relative to the one or more cameras) of a number of points that correspond to objects that are depicted in images captured by one or more cameras. Other sensors can identify the location of points that correspond to objects as well. Sensor fusion may be used to merge related data, such as from a time-of-flight (TOF) sensor to provide additional data and analysis.

The map database may provide detailed information associated with the map, features of the roadway in the geographic location, and information about the surrounding environment of the AV for the AV to use while driving (e.g., traversing a route, planning a route, determining a motion plan, controlling the AV, etc.).

The vehicle computing system may receive a vehicle pose from localization system based on one or more sensors that are coupled to or otherwise included in AV. The localization system may include a LIDAR localizer, a low-quality pose localizer, and/or a pose filter. For example, the localization system may employ a pose filter that receives and/or determines one or more valid pose estimates (e.g., not based on invalid position data, etc.) from the LIDAR localizer and/or a low-quality pose localizer, for determining a map-relative vehicle pose. For example, the low-quality pose localizer determines a low quality pose estimate in response to receiving position data from positioning system for operating (e.g., routing, navigating, controlling, etc.) the AV under manual control (e.g., in a coverage lane). The LIDAR localizer may determine a LIDAR pose estimate in response to receiving sensor data (e.g., LIDAR data, RADAR data, etc.) from sensors for operating (e.g., routing, navigating, controlling, etc.) the AV under autonomous control (e.g., in a coverage lane).

A vehicle command system may include a navigation system, and a lane association system that cooperate to route and/or navigate the AV in a geographic location. The vehicle command system may track a current objective of the AV, including a current service, a target pose, and/or a coverage plan (e.g., development testing, etc.). The navigation system may determine and/or provide a route plan (e.g., a task plan) for the AV based on the current state of the AV, map data (e.g., lane graph, etc.), and one or more vehicle commands (e.g., a target pose). For example, navigation system may determine a route plan (e.g., plan, re-plan, deviation, etc.) including one or more lanes (e.g., current lane, future lane, etc.) in one or more roadways the AV may traverse on a route to a destination (e.g., target, trip drop-off, etc.).

The navigation system may determine a route plan based on one or more lanes received from lane association system. The lane association system may determine one or more lanes of a route in response to receiving a vehicle pose from the localization system. For example, the lane association system determines, based on the vehicle pose, that the AV is on a coverage lane, and in response to determining that the AV is on the coverage lane, determines one or more candidate lanes (e.g., routable lanes) within a distance of the vehicle pose associated with the AV. For example, the lane association system determines, based on the vehicle pose, that the AV is on an AV lane, and in response to determining that the AV is on the AV lane, determines one or more candidate lanes (e.g., routable lanes) within a distance of the vehicle pose associated with the AV. The navigation system generates a cost function for each of one or more candidate lanes the AV may traverse on a route to a destination. For example, navigation system generates the cost function that describes a cost (e.g., a cost over a time period) of following (e.g., adhering to) one or more lanes to reach a target pose.

The perception system may detect and/or track objects (e.g., vehicles, pedestrians, bicycles, and/or the like) that are proximate to (e.g., in proximity to the surrounding environment of) the AV over a time period. The perception system can retrieve (e.g., obtain) map data from map database that provides detailed information about the surrounding environment of the AV. For example, the perception system may determine differences between the map data and a current sensor stream, and thereby infer mobile or dynamically changing elements and static elements. This, in turn, permits a risk assessment with respect to change of position or orientation of objects and their potential interaction with the AV during travel.

The perception system may determine one or more objects that are proximate to AV based on sensor data received from one or more sensors and/or map data from the map database. For example, the perception system determines, for the one or more objects that are proximate, state data associated with a state of such object. The state data associated with an object includes data associated with a location of the object (e.g., a position, a current position, an estimated position, etc.), data associated with a speed of the object (e.g., a magnitude of velocity of the object), data associated with a direction of travel of the object (e.g., a heading, a current heading, etc.), data associated with an acceleration rate of the object (e.g., an estimated acceleration rate of the object, etc.), data associated with an orientation of the object (e.g., a current orientation, etc.), data associated with a size of the object (e.g., a size of the object as represented by a bounding shape such as a bounding polygon or polyhedron, a footprint of the object, etc.), data associated with a type of the object (e.g., a class of the object, an object with a type of vehicle, an object with a type of pedestrian, an object with a type of bicycle, etc.), and/or the like.

The perception system may determine state data for an object over a number of iterations of determining state data. For example, perception system may update the state data for each object of a plurality of objects during each iteration.

The prediction system may receive the state data associated with one or more objects from perception system. The prediction system may predict one or more future locations for the one or more objects based on the state data. For example, the prediction system may predict the future location of each object of a plurality of objects within a time period (e.g., 0.5 second, 1 second, 2, seconds, 3 seconds, 4 seconds, 5 seconds, 10 seconds, 20 seconds, etc.). The prediction system may predict that an object will adhere to the object's direction of travel according to the speed of the object. The prediction system may use machine learning techniques or modeling techniques to make a prediction based on state data associated with an object.

The motion planning system may determine a motion plan for AV based on a prediction of a location associated with an object provided by the prediction system and/or based on state data associated with the object provided by the perception system. For example, the motion planning system may determine a motion plan (e.g., an optimized motion plan) for the AV that causes AV to travel relative to the object based on the prediction of the location for the object provided by the prediction system and/or the state data associated with the object provided by the perception system.

The motion planning system may receive a route plan as a command from the navigation system. The motion planning system may determine a cost function for each of one or more motion plans of a route for AV based on the locations and/or predicted locations of one or more objects. The cost function includes such parameters as time, objective, energy cost, safety risk, event cost, vehicle operation cost (e.g., tires, brakes, fuel/electricity), etc.

For example, the motion planning system determines the cost function that describes a cost (e.g., a cost over a time period) of following (e.g., adhering to) a motion plan (e.g., a selected motion plan, an optimized motion plan, etc.) as well as a predicted risk and associated costs of the predicted risks. The cost associated with the cost function increases and/or decreases based on elements of a motion plan (e.g., a selected motion plan, an optimized motion plan, a preferred motion plan, etc.).

For example, while a non-risk adjusted cost function increases and/or decreases based on the AV deviating from the motion plan to avoid a collision with an object, a risk adjusted cost function would generally decreased as a result of properly executed collision avoidance maneuvers. More generally, the risks are less discrete. Any time an AV changes lanes, there is a potential risk, though in some cases, the risk of changing lanes is lower than the risk or cost-compensated risk of remaining in the same lane. That is, the collision or adverse event is a low probability, but not zero, and the risk probability is generally included in the motion plan to mitigate unnecessary risks that do not substantially improve task efficiency. However, where task efficiency value of an action is substantial, and exceeds the risk-adjusted cost of the action, then the system should take the action.

The motion planning system may determine a cost of following a motion plan. For example, motion planning system determines a motion plan for AV based on one or more cost functions. The motion planning system determines a motion plan (e.g., a selected motion plan, an optimized motion plan, a preferred motion plan, etc.) that minimizes a risk-adjusted cost function. The motion planning system may provide a motion plan to vehicle controls (e.g., a device that controls acceleration, a device that controls steering, a device that controls braking, an actuator that controls gas flow, etc.) to implement the motion plan. Alternately, the motion planner may be integrated into the motion controller, and the plan need not be a separate and discrete communication.

Each main process within the system may be associated with its physical processor, instructions, memory, data communication interface, etc., or multiple functions may be combined in a single hardware platform. Typically, in order to guaranty deterministic performance, assist in achieving fault tolerance, provide opportunity for diagnostics, repair, and upgrades, separate hardware is provided for specific tasks, and the communications between the modules is discrete.

In a typical module, a bus permits communication among the components. The processor is implemented in hardware, firmware, or a combination of hardware and software. For example, processor includes one or more processing elements (e.g., a central processing unit (CPU), a graphics processing unit (GPU), an accelerated processing unit (APU), etc.), a microprocessor, a digital signal processor (DSP), and/or any processing component (e.g., a field-programmable gate array (FPGA), an application-specific integrated circuit (ASIC), etc.) that can be programmed to perform a function. A memory may include random access memory (RAM), read only memory (ROM), and/or another type of dynamic or static storage device (e.g., flash memory, magnetic memory, optical memory, etc.) that stores information and/or instructions for use by the processor.

A storage component stores information and/or software related to the operation and use of device. For example, the storage component includes a solid state mass storage device such as a NVMe®, PCIe 3.0 or PCIe 4.0 storage device.

An input component may include a component that permits the device to receive information, such as via user input (e.g., a touch screen display, a keyboard, a keypad, a mouse, a button, a switch, a microphone, etc.). Additionally, or alternatively, the input component includes a sensor for sensing information (e.g., a global positioning system (GPS) component, an accelerometer, a gyroscope, an actuator, etc.).

An output component may include a component that provides output information from the device (e.g., a display, a speaker, one or more light-emitting diodes (LEDs), etc.).

A communication interface may include a transceiver-like component (e.g., a transceiver, a separate receiver and transmitter, etc.) that enables the device to communicate with other devices, such as via a wired connection, a wireless connection, or a combination of wired and wireless connections. The communication interface can permit the device to receive information from another device and/or provide information to another device. For example, the communication interface may include an Ethernet interface, an optical interface, a coaxial interface, an infrared interface, a radio frequency (RF) interface, a universal serial bus (USB) interface, a Wi-Fi interface, a cellular network interface, and/or the like.

The device can perform one or more processes described herein, e.g., by executing software instructions stored by a computer-readable medium, such as a memory and/or the storage component. A computer-readable medium (e.g., a non-transitory computer-readable medium) is defined herein as a non-transitory memory device. A memory device includes memory space located inside of a single physical storage device or memory space spread across multiple physical storage devices. Software instructions can be read into the memory and/or storage component from another computer-readable medium or from another device via communication interface. When executed, software instructions stored in the memory and/or storage component cause the processor to perform one or more processes described herein. Additionally, or alternatively, hardwired circuitry can be used in place of or in combination with software instructions to perform one or more processes described herein. Thus, embodiments described herein are not limited to any specific combination of hardware circuitry and software.

The roadway may be associated with map data (e.g., map data, AV map data, coverage map data, hybrid map data, submap data, route data, etc.) that defines one or more attributes of (e.g., metadata associated with) the roadway (e.g., attributes of a roadway in a geographic location, attributes of a segment of a roadway, attributes of a lane of a roadway, attributes of an edge of a roadway, etc.). An attribute of a roadway may include a road edge of a road (e.g., a location of a road edge of a road, a distance of location from a road edge of a road, an indication whether a location is within a road edge of a road, etc.), an intersection, connection, or link of a road with another road, a roadway of a road, a distance of a roadway from another roadway (e.g., a distance of an end of a lane and/or a roadway segment or extent to an end of another lane and/or an end of another roadway segment or extent, etc.), a lane of a roadway of a road (e.g., a travel lane of a roadway, a parking lane of a roadway, a turning lane of a roadway, lane markings, a direction of travel in a lane of a roadway, etc.), one or more objects (e.g., a vehicle, vegetation, a pedestrian, a structure, a building, a sign, a lamppost, signage, a traffic sign, a bicycle, a railway track, a hazardous object, etc.) in proximity to and/or within a road (e.g., objects in proximity to the road edges of a road and/or within the road edges of a road), a sidewalk of a road, and/or the like.

The lane (and/or a roadway segment or extent) may have one or more ends. For example, an end of a lane (and/or a roadway segment or extent) is associated with or corresponds to a geographic location at which map data associated with the lane (and/or the roadway segment or extent) ends (e.g., is unavailable). As an example, an end of a lane can correspond to a geographic location at which map data for that lane ends.

The map data may include a link (e.g., a connection) that connects or links a lane (and/or a roadway segment or extent) to another lane (and/or to another roadway segment or extent). As an example, the map data includes a unique identifier for each lane (and/or roadway segment or extent), and the unique identifiers are associated with one another in the map data to indicate a connection or link of a lane to another lane (or a connection or link of a roadway segment or extent to another roadway segment or extent). For example, the unique identifiers can be associated with one another in the map data to indicate that a lane (and/or a roadway segment or extent) is a predecessor lane or a successor lane to another lane (and/or a predecessor or successor roadway segment or extent to another roadway segment or extent). As an example, a heading of travel (e.g., direction) of a predecessor lane to another lane is from the predecessor lane to another lane, and a heading of travel of a successor lane to another lane is from another lane to the successor lane.

The process includes determination of a driving path including one or more trajectories. The map generation system may determine a driving path including one or more trajectories for an AV in a roadway based on one or more traversals of the roadway by one or more vehicles. For example, the map generation system may determine a driving path in the roadway to represent an indication of a centerline path in at least one lane of the roadway for controlling the AV during operation (e.g., follow) on the driving path. As an example, map generation system may determine the centerline path based on the lane markings on the road and/or based on one or more traversals of the roadway by one or more vehicles and/or a determination of where a vehicle will drive in a lane of the roadway. The map generation system may determine a driving path that includes feature information based on features of the roadway (e.g., section of curb, marker, object, etc.) for controlling an AV to autonomously determine objects in the roadway. For example, the map generation system determines a driving path that includes the left and right edges of a lane in the roadway; in this way, the map generation system determines a driving path to control the AV in a roadway that includes a position of features (e.g., a portion of the feature, a section of the feature) in the roadway, while road edges and control measures may remain unchanged. As an example, the map generation system determines a driving path including feature information associated with lateral regions, for example, by determining the features of the roadway in the lateral regions. The map generation system may determine an entry point and end point of the driving path that is associated with entry information and/or end (e.g., exit) information for traversing the driving path, the entry and/or end information comprising at least one of heading information, curvature information, and acceleration information of the driving path.

The map generation system may determine a driving path in a lane in the geographic location that includes a first trajectory (e.g., a spline, a polyline, etc.); as an example, the map generation system may determine a single trajectory for a driving path in the roadway and/or a plurality of trajectories (e.g., a spline, a polyline, etc.) for a driving path in the roadway. As an example, the map generation system determines at least one trajectory of a driving path based on features in the roadway and/or traversals of the roadway by one or more vehicles (e.g., straightaways where paint lines are present, straight through intersections, straightaways where paint lines are not present, placement informed by average vehicle paths data, etc.) and/or the like. The map generation system may determine a trajectory for a driving path based on information obtained from a vehicle (e.g., autonomous vehicles, non-autonomous vehicles, etc.) representing a path in the roadway. For example, the map generation system may obtain information for determining a driving path based on one or more trajectories of the roadway associated with one or more traversals of the roadway by one or more vehicles (e.g., autonomous vehicles, non-autonomous vehicles, etc.), a number of traversals of the roadway by one or more vehicles, a position of the vehicle associated with one or more traversals, interventions associated with one or more traversals of the roadway by one or more vehicles, a number of objects (e.g., a number of hazards, a number of bicycles, a railway track in proximity to the roadway, etc.) associated with one or more traversals of the roadway by one or more vehicles, a distance and/or position (e.g., a vehicle pose, an average distance to a vehicle pose, a mileage, etc.) associated with one or more traversals of the roadway by one or more vehicles (e.g., a distance until a detection of an event, a distance until detection of a potentially harmful or a harmful event to an AV, to a rider of the AV, to a pedestrian, a distance between a first detection of an event and a second detection of an event, miles per event, etc.), one or more traffic controls of the roadway associated with one or more traversals of the roadway by one or more AVs, one or more aspects of the roadway (e.g., a dimension of one or more lanes of the roadway, a width of one or more lanes of the roadway, a number of bicycle lanes of the roadway, etc.) associated with one or more traversals of the roadway by one or more AVs, a speed of one or more AVs associated with one or more traversals of the roadway by the one or more AVs, and/or the like.

The map generation system may determines a single trajectory for at least one lane in the roadway and/or a driving path based on information including LIDAR point cloud maps (e.g., map point data, etc.) associated with a geographic location (e.g., a location in three-dimensional space relative to the LIDAR system of a mapping vehicle) of a number of points (e.g., a point cloud) that correspond to objects that have reflected a ranging laser of one or more mapping vehicles at the geographic location. As an example, a map can include a LIDAR point cloud layer that represents objects and distances between objects in the geographic location of the map.

The map generation system may include a driving path that includes a primary path in the driving path, the primary path including a first trajectory of the driving path. For example, map generation system may determine a primary path in the driving path by identifying that the primary path satisfies a threshold indicating a driving path for controlling the AV in an autonomous mode. For example, the primary path may be based on information indicating a path for an AV to autonomously follow. The map generation system may determine a secondary path in the driving path. For example, the map generation system may determine a secondary path identifying a trajectory in the driving path that may not satisfy a threshold indicating a driving path for controlling the AV to traverse the path autonomously (lanes where a driving path does not need to be clearly defined, turning lanes in intersections, defined turns in intersections, diverging/converging lanes, etc.).

For example, the map generation system may determine a secondary driving path that AV cannot operate on (e.g., drive) under the fully-autonomous mode. For example, map generation system may determine the secondary path in the driving path as an estimate of where an AV may drive. The proposal of a primary path or secondary path may be dependent on a safety factor, and therefore the safety determination is not limited to autonomous modes only, and rather may also predict manual or semi-automated safety parameters.

The map generation system may determine a driving path linking a first and a second driving path (e.g., a primary path to a primary path, a primary path to a secondary path, a secondary path to a primary path, etc.). For example, the first trajectory and second trajectory in the primary path each include an end point that is linked (e.g., logically connected) by the map generation system. The map generation system may determine a link for the first trajectory based on attributes of the point (e.g., an entry point of the trajectory, an end point of the trajectory), for example a position of a point, a heading of the trajectory at a point, an acceleration at a point (e.g., an entry point of the trajectory, an end point of the trajectory), and/or a curvature at a point (e.g., an entry point of the trajectory, an end point of the trajectory), and/or the like. For example, map generation system may determine a driving path that includes a first trajectory in a primary path linked to a second trajectory in a primary path, as a predecessor driving path (e.g., trajectory) to a successor driving path (e.g., trajectory), the link having continuity to generate the logical connection between the primary and secondary lane, in this way, providing continuity for one or more of a position of the endpoint, a heading of the trajectory at the end point, an acceleration at the end point, and a curvature at the end point. The map generation system may determine a link (e.g., logical connection) including continuity of a heading and/or a curvature associated with an entry point of the secondary path in the driving path for the heading and curvature associated with an end point of the primary path. In another example, the map generation system may determine a link (e.g., logical connection) that includes continuity of a heading and/or a curvature associated with an entry point of the primary path in the driving path to the heading and curvature associated with an end point of the secondary path. The map generation system may determine a primary driving path to include not more than one predecessor primary driving path linked to one successor primary driving path. The map generation system may determine continuity to provide a transition between a first driving path and a second driving path. The map generation system may determine a link between a first point and a second point, based on one or more attributes, for example, to provide logical connections to enhance the transition (e.g., smooth) across the link.

See, US 20200401145. See also, U.S. Pat. Nos. 4,296,901; 4,833,469; 4,940,925; 5,281,901; 5,341,130; 5,375,059; 5,390,125; 5,402,355; 5,438,517; 5,548,516; 5,610,815; 5,612,883; 5,629,855; 5,640,323; 5,646,843; 5,650,703; 5,657,226; 5,680,306; 5,684,696; 5,747,683; 5,838,562; 5,938,710; 5,995,882; 6,069,420; 6,122,572; 6,151,539; 6,269,763; 6,351,697; 6,393,362; 6,442,456; 6,799,100; 6,804,607; 7,047,888; 7,302,316; 7,335,067; 7,343,232; 7,494,090; 7,496,226; 7,542,828; 7,591,630; 7,693,624; 7,737,878; 7,844,396; 7,911,400; 7,949,541; 7,979,172; 7,979,173; 7,991,505; 8,060,271; 8,068,949; 8,103,398; 8,109,223; 8,126,642; 8,255,092; 8,280,623; 8,301,326; 8,355,834; 8,364,334; 8,412,449; 8,437,875; 8,437,890; 8,442,713; 8,577,538; 8,583,313; 8,606,589; 8,612,084; 8,706,394; 8,744,648; 8,751,143; 8,755,997; 8,755,999; 8,768,555; 8,784,034; 8,798,828; 8,843,244; 8,880,287; 8,935,071; 8,947,531; 8,948,955; 8,954,194; 8,988,524; 9,097,800; 9,120,484; 9,120,485; 9,139,363; 9,140,814; 9,199,667; 9,201,421; 9,201,424; 9,202,382; 9,208,456; 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It is an object to provide a method of operating a vehicle, comprising: planning motion of the vehicle, comprising computing motion trajectories of an action to incrementally advance the vehicle toward a goal with an associated incremental utility, based on at least a safety with respect to an environment of operation of the computed motion trajectories; and planning the task for the vehicle, comprising defining the goal and a sequence of the actions to advance the vehicle toward the goal, selectively dependent an optimization of an aggregate prospective utility of the task and the safety of the motion trajectories to advance the vehicle toward the goal.

It is also an object to provide a non-transitory computer readable medium containing a program for operating a vehicle, comprising: instructions for planning motion of the vehicle, comprising computing motion trajectories of an action to incrementally advance the vehicle toward a goal with an associated incremental utility, based on at least a safety with respect to an environment of operation of the computed motion trajectories; and instructions for planning the task for the vehicle, comprising defining the goal and a sequence of the actions to advance the vehicle toward the goal, selectively dependent an optimization of an aggregate prospective utility of the task and the safety of the motion trajectories to advance the vehicle toward the goal.

It is another object to provide a system for operating a vehicle, comprising: a sensor configured to receive information about an environment of operation of the vehicle; at least one automated processor; a motion planner configured to plan a motion of the vehicle, configured to compute motion trajectories with the at least one automated processor, an action to incrementally advance the vehicle toward a goal with an associated incremental utility, based on at least a safety of the motion trajectories with respect to an environment of operation of the vehicle; and a task planner configured to plan the task for the vehicle with the at least one automated processor, comprising defining the goal and a sequence of the actions to advance the vehicle toward the goal, selectively dependent an optimization of an aggregate prospective utility of the task and the safety of the motion trajectories to advance the vehicle toward the goal.

It is a further object to provide a method of operating an autonomous vehicle, comprising: determining a safety of motion of the autonomous vehicle in an environment dependent on real-time conditions of operation; planning a route for the autonomous vehicle selectively dependent on the determined safety of motion of the autonomous vehicle in the environment and optimization of a utility of the planned route; planning the motion of the autonomous vehicle according to the planned route, comprising selecting motion options consistent with the planned route that are safe with respect to the environment dependent on real-time conditions of operation, wherein the planned route is responsive to the planned motion; and controlling the autonomous vehicle according to the planned route and planned motion.

A further object provides a method of controlling an autonomous vehicle, comprising: receiving data relating to a relationship of the autonomous vehicle with respect to the environment; determining a motion and environment-dependent safety of the autonomous vehicle within an environment of operation; continuously planning a utility-optimized route for an autonomous vehicle along a path having execution options within the route, updated dependent on the determined motion and environment-dependent safety of the autonomous vehicle; continuously planning the motion of the autonomous vehicle according to the planned utility-optimized route, comprising selection of the execution options which alter a relation of the autonomous vehicle with the environment, that meet at least one safety criterion with respect to the determined a motion and environment-dependent safety; and controlling the autonomous vehicle according to the planned utility-optimized route and planned motion, to thereby achieve safe and efficient travel of the autonomous vehicle.

Another object provides a method of operating a vehicle, comprising: planning a task for the vehicle, comprising a safe sequence of actions to accomplish goals which optimize the task; and planning motion of the vehicle, comprising computing motion trajectories that connect a current location with a goal location, based on at least safety with respect to surrounding vehicles.

It is an object of the invention to provide a method of operating a vehicle, comprising: planning motion of the vehicle, comprising computing motion trajectories that connect a current location with a goal location determined according to a planned task, based on a utility optimization of vehicle motion based on at least safety with respect to an environment of operation; and planning the task for the vehicle, comprising a sequence of actions to accomplish goals, selectively dependent on at least the safety.

It is an object to provide a non-transitory computer readable medium containing a program for operating a vehicle, comprising: instructions for planning motion of the vehicle, comprising computing motion trajectories that connect a current location with a goal location according to a planned task, based on a utility optimization of vehicle motion based on at least safety with respect to an environment of operation; and instructions for planning the task for the vehicle, comprising a sequence of actions to accomplish goals, selectively dependent in at least the safety.

It is a further object to provide a system for operating a vehicle, comprising: a motion planner configured to plan a motion of the vehicle, according to computed motion trajectories that connect a current location with a goal location, based on a utility optimization of vehicle motion based on at least safety with respect to an environment of operation; and a task planner configured to plan the task for the vehicle, to define a sequence of actions to accomplish goals selectively dependent on at least the safety.

It is a still further object to provide a method of operating an autonomous vehicle, comprising: determining a safety of operation of the autonomous vehicle in an environment dependent on real-time conditions of operation; planning a route for the autonomous vehicle selectively dependent on the determined safety of operation in the environment; planning motion of the autonomous vehicle according to the planned route, comprising selection of options consistent with the route that optimize a utility function and a safety with respect to the environment selectively dependent on the determined safety of operation in the environment, wherein the planned route is responsive to the planned motion; and controlling the autonomous vehicle according to the planned route and planned motion.

The selected options may be responsive to a cost of a maneuver, a benefit of the maneuver, and a determined safety of the maneuver.

The method may further comprise updating the planning of the route based on the planned motion in real time.

The safety of operation may be determined statistically based on a predicted risk.

The safety of operation may be determined based on a risk of collision.

It is another object to provide a method of controlling an autonomous vehicle, comprising: receiving data relating to a relationship of the autonomous vehicle with respect to the environment; determining a motion and environment-dependent safety of the autonomous vehicle within an environment of operation; continuously planning a route for an autonomous vehicle along a path having execution options within the route, updated dependent on the determined motion and environment-dependent safety of the autonomous vehicle; continuously planning motion of the autonomous vehicle according to the planned route, comprising selection of the execution options which alter a relation of the autonomous vehicle with the environment, that meet at least one utility criterion and at least one safety criterion; and controlling the autonomous vehicle according to the planned route and planned motion, to thereby achieve safe and efficient travel of the autonomous vehicle.

The safety may be determined based on various sensors, such as radar, lidar, video cameras, sonar, inertial sensors, OBD-II data stream (see, en.wikipedia.org/wiki/On-board_diagnostics, CANbus, ISO 15765-4), weather sensors, on-line social network database, real time traffic information database, and/or based on intervehicle communications, for example.

Where explicit intervehicle communications are supported, the task plan, the motion plan, or both may be coordinated between vehicles, either in a centralized or decentralized manner, using vehicle-to-vehicle communications. Further, sensor data may be relayed between vehicles to provide advance warning, especially to the task planner, though in some cases, short latency warnings and environmental conditions may have direct impact on the motion planning.

The environmental conditions may be local vehicular motion of another vehicle, weather conditions (rain, puddles, sun glare, black ice, snow, freezing conditions, tornado warning, hail, etc.), traffic, history of incidents (e.g., accidents, emergency maneuvers, law enforcement) at a location, obstacles and hazards at a location (e.g., detours, potholes, obstructed vision, pedestrians and cyclists, animals, children playing), etc.

In a typical case, the autonomous vehicle in a lane catches up to another vehicle travelling slower in the same lane. The motion planner considers the option of switching lanes, which may reduce overall travel time (i.e., increase efficiency), but may also lead to other obstructions in the lane, and incurs a collision risk dependent on other vehicles surrounding the autonomous vehicle. Therefore, both the incremental maneuver by the motion planner of changing lanes, and the larger plan of increasing efficiency according to a cost function or utility function, are each dependent on the safety of the autonomous vehicle. The motion planner is principally concerned with the safety of the autonomous vehicle during the maneuver, while the task planner is concerned with the change in safety before and after the maneuver, as well as the predicted safety during the maneuver and predicted safety after the maneuver. The task planner may, for example, consider distance and time, two likely important (but non-excusive) determinates of utility, which in some cases could lead to a selection of a completely different route. Other utility issues are fuel consumption, fuel availability, tolls, availability of services such as food and lodging for extended trips with human passengers, and the like.

The planning of the task may comprise specifying a task planning domain by D^t, including a set of states, S, and a set of actions, A; providing a factored state space such that each state $s \in S$ is defined by values of a fixed set of variables, and each action $a \in A$ is defined by its preconditions and effects; and defining a utility function which maps a state transition to a real number, which takes both a cost function Cost(s, a,s') and a safety function Safe(s,a,s') of conducting action a in state s into account.

The method may further comprise computing a plan $p \in P$, given domain D^t and a task planning problem, is computed, starting from an initial state $s^{init} \in S$ and finishing in a goal state $s^g \in S$; representing a plan p, consisting of a sequence of transitions represented as $p = \langle s_0, a_0, \ldots, s_{N-1}, a_{N-1}, s_N \rangle$, where $s_0 = s^{init}$, $s^N = s^g$ and P denotes a set of satisfactory plans; and producing an optimal plan p* with a task planner P^t among all the satisfactory plans, where γ is a constant coefficient and $\gamma > 0$,

$$p^* = \operatorname*{argmin}_{p \in P} \sum_{\langle s,a,s' \rangle \in p} \left[\mathrm{Cost}(\langle s, a, s' \rangle) + \frac{\gamma}{1 + e^{Safe(\langle s,a,s' \rangle) - 1}} \right].$$

The method may further comprise conducting a search directly in a two-dimensional Cartesian space such that a position and an orientation of the vehicle is uniquely represented as a pose, denoted by x and constrained by the urban road network, wherein some parts of the space are designated as free space, and remaining parts are designated as obstacles, and a motion planning domain is specified by D^m, wherein given domain D^m, a motion planning problem is specified by an initial pose x^i and a goal pose x^g.

The method may further comprise planning the motion by a motion planner P^m consisting of a path planner and a tracking planner into two phases, wherein: in a first phase, the path planner computes a collision-free trajectory ξ connecting pose x^i and pose x^g taking into account any motion constraints on the part of the vehicle with a minimal trajectory length; and in a second phase, computing control signals with a tracking controller to drive the vehicle to follow the computed trajectory.

The method may further comprise mapping a systolic state s with a state mapping function, f:X=f(s), into a set of feasible poses X in a continuous space as available options for the motion planner, wherein availability of at least one pose x∈X is assumed in each state s, such that the vehicle is in a free space of D^m, and if it is not in a free space of D^m, the state s is declared infeasible.

The method may further comprise computing a safety level, Safe(⟨s,a,s'⟩), of a motion-level implementation of a symbolic action ⟨s,a,s'⟩, wherein the safety level enables the task planner to incorporate a road condition into a process of sequencing high-level actions toward accomplishing complex driving tasks.

The method may further comprise computing a sequence of continuous control signals to perform symbolic action ⟨s,a,s'⟩, comprising an acceleration δ∈Δ and steering angle θ∈Θ, to drive the vehicle following a trajectory, while ensuring no collision on the road, wherein sets Δ and Θ denote an operation specification of the tracking controller. $U_s(t)\subset\Delta\times\Theta$ may specify a safe control set at time t, in which all elements, denoted by u(t)=⟨δ,θ⟩, are safe for the vehicle to perform at time t, such that a probability of elements sampled from set Δ×Θ being located in the safe set U_s represents the safety value of action ⟨s,a,s'⟩.

The method may further comprise:

- receiving an input which includes a symbolic action ⟨s,a,s'⟩, stating mapping function f, motion planner P^m consisting of path planner and tracking controller, and a tracking controller's operation specification sets Δ and Θ;
- obtaining short-period trajectories of the vehicle and surrounding vehicles, where V_i,i∈[1, . . . , N], is the ith vehicle within a sensing range of the vehicle;
- iteratively:
  - computing a safety estimation between the vehicle and the surrounding vehicles V_i, where i∈[1, . . . , N], given that the vehicle is performing action ⟨s,a,s'⟩, at a motion level;
  - computing a safe control set $U_i^s(t)$ that includes all safe control signals with regard to the vehicle V_i at time t;
  - randomly sampling M elements from the set Δ×Θ, and computing a probability $o_i(t)$ of the sampled elements falling in set $U_i^s(t)$;
  - converting a list of values of safety estimation $\{o_i(t)\}$ into a single value o^*_i according to

$$o_i^* = \frac{\max_{t\in T}\{o_i(t)\} + mean_{t\in \mathcal{T}}\{o_i(t)\}}{2};$$

and

- selecting a minimum value o^*_i,i∈[1, . . . , N], as an overall safety value, where $\mathcal{T}=t_1+\omega\times i$,

$$0 \le i \le \frac{(t_2-t_2)}{\omega};$$

and

- producing an output of an estimated safety value Safe(⟨s,a,s'⟩)∈[0.0,1.0].

The method may further comprise:

- receiving inputs: Symbolic action ⟨s,a,s'⟩, state mapping function f, motion planner P^m, control operation sets Δ and Θ;
- sampling initial and goal poses, x←f(s) and x'←f(s'), given action ⟨s,a,s'⟩, and f;
- computing a collision-free trajectory, ξ^E, using P^m, where $\xi^E(t_1)$=x,$\xi(t_2)$=x'; and $[t_1,t_2]$ is the horizon;
- predicting a trajectory ξ_i^s for an ith surrounding vehicle V_i, where i∈[1, . . . , N], and $[t_1,t_2]$ is the horizon;
- for each surrounding vehicle V_i:
  - computing a safe control set $U_i^s(t)$ between the vehicle and vehicle V_i at time t∈$[t_1,t_2]$, where $U_i^s(t)\subset\Delta\times\Theta$ and

$$t = t_1 + \omega\times i,\ i \le \frac{(t_2-t_2)}{\omega};$$

- sampling M elements ⟨δ,θ⟩ randomly from set Δ×Θ and computing a probability $o_i(t)$ of the elements falling in set $U_i^s(t)$;
- converting a list of estimated safety values, $\{o_i(t)\}$, into a scalar value o^*_i using

$$o_i^* = \frac{\max_{t\in T}\{o_i(t)\} + mean_{t\in \mathcal{T}}\{o_i(t)\}}{2};$$

and

- selecting a minimum value, o^*_i,i∈[1, . . . , N], as a safety value.

A motion planner P^m may compute both costs and safety values of the vehicle's navigation actions; s^{init} may represent an initial state of the vehicle, and the goal of the task is specified using s^g; a task planner P^t may compute a sequence of symbolic actions, employing a cost function Cost, and a safety estimation function Safe; a motion planner P^m may be used for computing motion trajectories, and generating control signals to move the vehicle; and a state mapping function f used for mapping symbolic states to 2D coordinates in continuous spaces.

The method may further comprise: initializing a cost function and a safety estimation function; computing an optimal task plan, p*=⟨s^{init}, a_0, s_1, . . . , s^g⟩ wherein s^{init} and s^g correspond to initial and goal poses respectively; estimating a safety level, μ, of action ⟨s,a,s'⟩; updating the safety estimation function using u and the cost function using p*; and computing a new optimal plan p'.

A motion planner may compute and execute a desired control signal ⟨δ,θ⟩ repeatedly until the vehicle reaches the goal pose.

The method may further comprise:

- receiving inputs comprising: an initial state s^i, goal specification s^g, task planner P^t, state mapping function f, motion planner P^m, and safety estimator;
- initialize a cost function Cost with sampled poses x∈f(s):Cost(⟨s,a,s'⟩)←A*(x,x');
- initialize a safety estimation function Safe with Safe (s,a,s')←1.0.
- computing an optimal task plan p using Cost and Safe functions:
- p←P^t(s^{init}, s^g, Cost, Safe), where p=(s^{init}→a_0, s_1, a_1, . . . , s^g⟩
- until plan p is not empty:

extracting a first action of p, $\langle s,a,s'\rangle$, and computing a safety value μ;

updating the Safe function: Safe($\langle \in a, s'\rangle$)←μ and the Cost function:

$$\mathrm{Cost}(\langle s,a,s'\rangle)\leftarrow A^*(x,x')$$

generating a new plan: p'←P^t(s, s^g, Cost, Safe);

if p'==p then x'←f(s'), and while x!=x', call a motion planner $\langle \delta,\theta\rangle \leftarrow P^m(x,x')$, execute a control signal $\langle \delta,\theta\rangle$, and update the vehicle's current pose x;

removing a tuple $\langle s,a\rangle$ from plan p;

else updating current plan p←p'.

The task planner P^t may be implemented using Answer Set Programming (ASP).

The environment of operation may comprise surrounding vehicles, e.g., vehicles in motion.

The utility optimization may comprise minimizing a travel distance while maintaining a margin of safety.

It is also an object to provide a method of operating a vehicle, comprising: planning a task for the vehicle, comprising an efficient sequence of actions to accomplish goals, e.g., according to action knowledge; and planning motion of the vehicle, comprising computing motion trajectories that efficiently connect a current location with a goal location, based on at least surrounding vehicles to ensure safety.

It is a further object to provide a non-transitory computer readable medium containing a program for operating a vehicle, comprising: instructions for planning a task for the vehicle, comprising an efficient sequence of actions to accomplish goals, e.g., according to action knowledge; and instructions for planning motion of the vehicle, comprising computing motion trajectories that efficiently connect a current location with a goal location, based on at least surrounding vehicles to ensure safety.

It is a still further object to provide a system for operating a vehicle, comprising: a task planner configured to plan a task for the vehicle, to define an efficient sequence of actions to accomplish goals, e.g., according to action knowledge; and a motion planner configured to plan motion of the vehicle, according to computed motion trajectories that efficiently connect a current location with a goal location, based on at least surrounding vehicles to ensure safety.

Another object provides a method of operating a vehicle, comprising: planning a task for the vehicle, comprising a sequence of actions to accomplish goals, e.g., according to action knowledge; and planning motion of the vehicle, comprising computing motion trajectories that connect a current location with a goal location, based on a cost optimization of vehicle motion based at least safety with respect to surrounding vehicles.

A further object comprises a non-transitory computer readable medium containing a program for operating a vehicle, comprising: instructions for planning a task for the vehicle, comprising a sequence of actions to accomplish goals, e.g., according to action knowledge; and instructions for planning motion of the vehicle, comprising computing motion trajectories that connect a current location with a goal location, based on a cost optimization of vehicle motion based on at least safety with respect to surrounding vehicles.

A still further object provides a system for operating a vehicle, comprising: a task planner configured to plan a task for the vehicle, to define a sequence of actions to accomplish goals, e.g., according to action knowledge; and a motion planner configured to plan motion of the vehicle, according to computed motion trajectories that connect a current location with a goal location, based on a cost optimization of vehicle motion based on at least safety with respect to surrounding vehicles.

An object further provides a method of operating an autonomous vehicle, comprising: planning a route for the autonomous vehicle; planning motion of the autonomous vehicle according to the planned route, comprising selection of options consistent with the route that are cost efficient and safe with respect to surrounding vehicles; and controlling the autonomous vehicle according to the planned route and planned motion.

A further object provides a method of controlling an autonomous vehicle, comprising: planning a route for the autonomous vehicle along a path having execution options within the route; receiving data relating to a relationship of the autonomous vehicle with respect to other vehicles along the route; planning motion of the autonomous vehicle according to the planned route, comprising selection of options consistent with the route and which alter a relation of the autonomous vehicle with the other vehicles, that are cost efficient and safe with respect to the other vehicles; and controlling the autonomous vehicle according to the planned route and planned motion comprising a selected option.

BRIEF DESCRIPTION OF THE DRAWINGS

FIGS. **1**A and **1**B show a risky situation for the vehicle to merge left due to the busy traffic (FIG. **1**A), and a safe situation for the vehicle to merge left (FIG. **1**B).

FIG. **2** shows an overview of the TMPUD algorithm that consists of four components, the task planner, plan manager, motion planner and safety estimator.

FIG. **3** shows an illustrative example of operation of the system, where the vehicle is tasked with driving from the very left to the top-right area.

FIGS. **4**A-**4**D show results of an abstraction simulation which compare the overall performances of TMPUD and two baseline methods.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Example 1

FIG. **2** shows an overview of algorithm TMPUD that consists of four components, i.e., task planner, plan manager, motion planner and safety estimator. The task planner includes components of goal specification, action description, and utility function, where users' service requests are received by the goal specification component. The task planner computes a sequence of symbolic actions that are passed to the plan manager. The plan manager generates navigation goals (i.e., a pair of two poses) to path planner, which is then used for computing a continuous trajectory for connecting 2D poses. The trajectory will be used in the two components of safety estimator and tracking controller. Safety estimator uses this trajectory to estimate actions' safety levels, and then the utility function in task planner can be updated accordingly. Tracking controller computes the desired control signals to drive the vehicle to follow the trajectory from the path planner.

FIG. **3**. An illustrative example, where the vehicle is tasked with driving from the very left to the top-right area. The vehicle needs to compute plans at both task and motion levels. The vehicle starts with executing Plan A (blue color). While it is getting close to Area **1** (a red circle), the motion-level safety estimator reports a low safety value based on the local road condition. This computed safety value is incorporated into task planner's cost function. Using the updated cost function, the task planner re-computes an optimal plan (Plan B), and suggests the vehicle to go straight and merge left in Area **2**. The interaction between task and motion levels, supported by TMPUD, enables the vehicle to dynamically adjust its high-level task plans to avoid unsafe behaviors.

TMPUD starts with using an optimal task planner to compute Plan A. The vehicle takes the first symbolic action from Plan A (trajectory in blue color), and executes the action using the motion planner. Getting close to Area **1**, the vehicle plans to merge left. However, the safety estimator at the motion level reports a low safety value in Area **1**. This computed safety value is incorporated into task planner, where the task planner integrates the safety value into its cost function, and re-computes an optimal plan, Plan B. Different from Plan A, Plan B suggests the vehicle to go straight, and merge left in Area **2**. In this trial, the vehicle was able to follow Plan B all the way to the goal. TMPUD enabled the vehicle to avoid the risky behavior of merging left in Area **1** without introducing extra motion cost. See, youtu.be/8NHQYUqMyoI.

Experiments conducted in CARLA are referred as being in full simulation. All vehicles move at a constant speed (20 km/h) on average. In full simulation, ego vehicle performs the whole plan at the task level in the presence of other vehicles. Different numbers of vehicles (200 and 120) are spawned, and traffic of the two environments referred to as being heavy and normal respectively.

Running full simulation using CARLA is time-consuming, preventing conducting of large-scale experiments. For instance, results are based on tens of thousands of experimental trials, and full simulation in this scale would have required months of computation time. To conduct large numbers of experimental trials, an abstract simulation platform was developed, where action outcomes are sampled from pre-computed probabilistic world models. Parameters of the world models (for abstract simulation) are learned by repeatedly spawning the ego and surrounding vehicles in a small area, and statistically analyzing the results of the vehicles' interaction.

In particular, a large effort was made in analyzing the outcomes of "merging lane" actions due to its significant potential risks. The probabilities of the three different outcomes of "merging lane" actions were empirically computed, including "merge", "collide", and "stop". Two domain factors were introduced into the abstract simulation platform, including density and acceleration. In high-density environments, the ego vehicle is surrounded by three vehicles, while this number is reduced to one in low-density environments. In high-acceleration environments, surrounding vehicles' acceleration (in m/s2) is randomly sampled in [−1.0, 1.0], while this range is [−0.5, 0.5] in low-acceleration environments.

The goal of TMPUD is to improve task-completion efficiency (to reduce traveling distance), while guaranteeing safety. So, the two most important evaluation metrics are traveling distance and the number of unsafe behaviors, where unsafe behaviors cause either collisions or force at least one surrounding vehicle to stop (to avoid collisions).

The two baseline methods are selected from the literature, and referred to as No-communication (No-com), and Threshold-based (Th-based). The No-com baseline [13] forces the vehicle to execute all task-level actions at the motion level, while driving behaviors' safety values are not considered. The Th-based baseline [8] enables the motion planner to "reject" a task-level action when its safety value is lower than a threshold β, where a higher (lower) β threshold makes a vehicle more conservative (aggressive). In case of an action being rejected, the task planner will compute a new plan to avoid the risky action. Three versions of the Th-based baseline were developed with different β values (0.1, 0.3, and 0.5).

TABLE I

FULL SIMULATION: TRAVELING DISTANCE AND NUMBER OF COLLISIONS AND STOPS FOR THREE ALGORITHMS UNDER DIFFERENT TRAFFIC CONDITIONS (NORMAL AND HEAVY TRAFFIC).

Algorithm		Travelling Distance (m)	Num. of collisions and stops
Normal Traffic			
TMPUD		514	0
Th-based	β = 0.5	537	0
	β = 0.3	513	5
	β = 0.1	478	24
No-com		426	48
Heavy Traffic			
TMPUD		530	2
Th-based	β = 0.5	545	2
	β = 0.3	528	7
	β = 0.1	497	35
No-com		426	54

Results from Full Simulation

Table I presents the results in comparing TMPUD to the two baseline methods. As shown in the table, in both road conditions, TMPUD achieved the lowest traveling distance, in comparison to those methods that produced compared safety levels (in terms of the number of collisions and stops). For instance, under normal traffic, only the Th-based baseline with β=0.5 was able to completely avoid collisions and stops, but it produced an average traveling distance of 537 m. In comparison, TMPUD required only 514 m, while completely avoided collisions and stops. Under heavy traffic, TMPUD (again) produced the best performance in safety (based on the number of collisions and stops), while requiring less traveling distance in comparison to the only baseline (Th-based with β=0.5) that produced comparable performance in safety. The experimental trials (200 for each approach) from full simulation took eight full workdays.

FIGS. **4A-4D** show abstraction simulation of the overall performances of TMPUD and two baseline methods. The x-axis represents the average traveling distance, and the y-axis represents the total number of collisions and stops. FIGS. **4A-4D** correspond to four different road conditions. The road conditions, low-density and low-acceleration (FIG. **4A**), low-density and high-acceleration (FIG. **4B**), high-density and low-acceleration (FIG. **4C**), high-density and high-acceleration (FIG. **4D**). Under each road condition, each algorithm was evaluated using 4000 trials. Batch-based evaluations were employed with four batches for significance analysis, where each batch includes 1000 trials.

Results from Abstract Simulation

FIGS. **4A-4D** present the performances of TMPUD and the baseline methods in both traveling distance and the number of unsafe behaviors. The x-axis corresponds to the average traveling distance, and y-axis corresponds to the total number of collisions and stops (both are considered failure cases of driving behaviors). From FIGS. **4A-4D**, TMPUD is shown to be the most efficient (x-axis) among those methods that produced comparable performances in safety (y-axis), except that Th-based (β=0.5) produced slightly less unsafe behaviors (but it performed poorly in efficiency).

There are a few side observations. Not surprisingly, No-com produced the worst performance of in safety (y-axis), though its traveling distance remains the lowest. This is because, using No-com, the vehicle blindly executes task-level actions while unrealistically believing driving behaviors are always safe. The Th-based baseline's performance depends on its safety threshold (β), where a greater value produces safer but less efficient behaviors. The results show that TMPUD improves vehicles' task-completion efficiency, while ensuring safety in different road conditions.

Focusing on urban driving scenarios, both a safety evaluation algorithm, and a task-motion planning algorithm, called TMPUD, are provided for autonomous driving. TMPUD bridges the gap between task planning and motion planning in autonomous driving. TMPUD was extensively evaluated using a 3D urban driving simulator (CARLA) and an abstract simulator. Results suggest that TMPUD improves the task-completion efficiency in different road conditions, while ensuring the safety of driving behaviors.

TMPUD may also be implemented using different task and motion planners, and these in turn may be evaluated in different testing platforms (e.g., using simulators with a physics engine) under different conditions. The technology may be applied to various autonomous mobile platforms, such as robots, drones.

A phrase such as an "aspect" does not imply that such aspect is essential to the subject technology or that such aspect applies to all configurations of the subject technology. A disclosure relating to an aspect may apply to all configurations, or one or more configurations. An aspect may provide one or more examples. A phrase such as an aspect may refer to one or more aspects and vice versa. A phrase such as an "embodiment" does not imply that such embodiment is essential to the subject technology or that such embodiment applies to all configurations of the subject technology. A disclosure relating to an embodiment may apply to all embodiments, or one or more embodiments. An embodiment may provide one or more examples. A phrase such an embodiment may refer to one or more embodiments and vice versa. A phrase such as a "configuration" does not imply that such configuration is essential to the subject technology or that such configuration applies to all configurations of the subject technology. A disclosure relating to a configuration may apply to all configurations, or one or more configurations. A configuration may provide one or more examples. A phrase such a configuration may refer to one or more configurations and vice versa.

Certain units described in this specification have been labeled as modules in order to more particularly emphasize their implementation independence. A module is "[a] self-contained hardware or software component that interacts with a larger system." Alan Freedman, "The Computer Glossary" 268 (8th ed. 1998). A module may include a machine- or machines-executable instructions. For example, a module may be implemented as a hardware circuit including custom VLSI circuits or gate arrays, off-the-shelf semiconductors such as analog circuits, quantum computers, microprocessors, logic chips, transistors, or other discrete components. A module may also be implemented in programmable hardware devices such as field programmable gate arrays, programmable array logic, programmable logic devices or the like.

Modules may also include software-defined units or instructions, that when executed by a processing machine or device, transform data stored on a data storage device from a first state to a second state. An identified module of executable code may, for instance, include one or more physical or logical blocks of computer instructions that may be organized as an object, procedure, or function. Nevertheless, the executables of an identified module need not be physically located together, but may include disparate instructions stored in different locations that, when joined logically together, include the module, and when executed by the processor, achieve the stated data transformation. A module of executable code may be a single instruction, or many instructions, and may even be distributed over several different code segments, among different programs, and/or across several memory devices. Similarly, operational data may be identified and illustrated herein within modules, and may be embodied in any suitable form and organized within any suitable type of data structure. The operational data may be collected as a single data set, or may be distributed over different locations including over different storage devices. The absence of a module reflects the inability of system including the module to execute in given circumstances to perform the function of the respective module, and not that its physical or logical constituents are excluded, that is, the module is unavailable. In the foregoing description, numerous specific details are provided, such as examples of programming, software modules, user selections, network transactions, distributed ledgers, blockchains, smart contracts, database queries, database structures, hardware modules, hardware circuits, hardware chips, etc., to provide a thorough understanding of the present embodiments. One skilled in the relevant art will recognize, however, that the invention requires a specific implementation that requires special purpose technology for implementation, that generic hardware alone will not achieve the objectives set forth herein.

As used herein, various terminology is for the purpose of describing particular implementations only and is not intended to be limiting of implementations. For example, as used herein, an ordinal term (e.g., "first," "second," "third," etc.) used to modify an element, such as a structure, a component, an operation, etc., does not by itself indicate any priority or order of the element with respect to another element, but rather merely distinguishes the element from another element having a same name (but for use of the ordinal term). The term "coupled" is defined as connected, although not necessarily directly, and not necessarily mechanically; two items that are "coupled" may be unitary with each other, but in that case the unitary element must meet established criteria for each item. The terms "a" and "an" are defined as one or more unless this disclosure explicitly requires otherwise. The term "substantially" is defined as largely but not necessarily wholly what is specified (and includes what is specified; e.g., substantially 90 degrees includes 90 degrees and substantially parallel includes parallel), as understood by a person of ordinary skill in the art.

The phrase "and/or" means "and" or "or". To illustrate, A, B, and/or C includes: A alone, B alone, C alone, a combination of A and B, a combination of A and C, a combination of B and C, or a combination of A, B, and C. In other words, "and/or" operates as an "inclusive or". Similarly, the phrase "A, B, C, or a combination thereof" or "A, B, C, or any combination thereof" includes A alone, B alone, C alone, a combination of A and B, a combination of A and C, a combination of B and C, or a combination of A, B, and C.

As used herein, whether in the above description or the following claims, the terms "comprising," "including," "carrying," "having," "containing," "involving," and the like are to be understood to be open-ended, that is, to mean including but not limited to. The terms "comprise" (and any form of comprise, such as "comprises" and "comprising"), "have" (and any form of have, such as "has" and "having"), and "include" (and any form of include, such as "includes" and "including"). As a result, an apparatus that "comprises," "has," or "includes" one or more elements possesses those one or more elements, but is not limited to possessing only those one or more elements. Likewise, a method that "comprises," "has," or "includes" one or more steps possesses those one or more steps, but is not limited to possessing only those one or more steps.

Some implementations are described herein in connection with thresholds. As used herein, satisfying a threshold may refer to a value being greater than the threshold, more than the threshold, higher than the threshold, greater than or equal to the threshold, less than the threshold, fewer than the threshold, lower than the threshold, less than or equal to the threshold, equal to the threshold, etc.

The terms "about" or "approximately" are intended to denote a range for a quantitative parameter that achieves substantially the same result in the same manner, with either a predictable relation between input parameter and behavior, a statistically insignificant change in response with respect to the change between a nominal input parameter and another input parameter within the stated range of "about" or "approximately". Thus, a feature would be outside a range of "about" or "approximately" if the result is achieved in a substantially different manner, a substantially different result is achieved, within the range statistically significant and meaningful differences in output response are achieved based on differences between the nominal parameter and the putative one which is "about" or "approximately" the same, or the result is unpredictable to an extent that the output response unpredictable deviates from the benchmark established. "Substantially" and "significant" are interpreted according to the understanding of persons of ordinary skill in the art, dependent on the context, and are intended to represent a reasonable range of quantitative difference which may be ignored or compensated without change in cause or effect.

It will be apparent that systems and/or methods, described herein, can be implemented in different forms of hardware, software, or a combination of hardware and software. The actual specialized control hardware or software code used to implement these systems and/or methods is not limiting of the implementations. Thus, the operation and behavior of the systems and/or methods are described herein without reference to specific software code, it being understood that software and hardware can be designed to implement the systems and/or methods based on the description herein. It is also understood that the algorithms are not limited by particular expressions, and rather are intended to encompass functional equivalents regardless of expression. Further, as is known and well understood, semantic expressions relating inputs or available data and output or action are themselves algorithms.

Even though particular combinations of features are recited in the claims and/or disclosed in the specification, these combinations are not intended to limit the disclosure of possible implementations. In fact, many of these features can be combined in ways not specifically recited in the claims and/or disclosed in the specification. Although each dependent claim listed below may directly depend on only one claim, the disclosure of possible implementations includes each dependent claim in combination with every other claim in the claim set.

No element, act, or instruction used herein should be construed as critical or essential unless explicitly described as such. Also, as used herein, the articles "a" and "an" are intended to include one or more items, and may be used interchangeably with "one or more." Furthermore, as used herein, the term "set" is intended to include one or more items (e.g., related items, unrelated items, a combination of related and unrelated items, etc.), and may be used interchangeably with "one or more." Where only one item is intended, the term "one" or similar language is used. Also, as used herein, the terms "has," "have," "having," and/or the like are intended to be open-ended terms. Further, the phrase "based on" is intended to mean "based, at least in part, on" unless explicitly stated otherwise.

Any embodiment of any of the systems, methods, and article of manufacture can "consist of" or "consist essentially of", rather than "comprise", "have", or "include", any of the described steps, elements, and/or features. Thus, in any of the claims, the term "consisting of" or "consisting essentially of" can be substituted for any of the open-ended linking verbs recited above, in order to change the scope of a given claim from what it would otherwise be using the open-ended linking verb. Thus, the transitional phrases "consisting of" and "consisting essentially of," respectively, shall be considered exclusionary transitional phrases, as set forth, with respect to claims, in the United States Patent Office Manual of Patent Examining Procedures. Additionally, the terms "wherein" or "whereby" may be used interchangeably with "where".

Further, a device or system that is configured in a certain way is configured in at least that way, but it can also be configured in other ways than those specifically described. The feature or features of one embodiment may be applied to other embodiments, even though not described or illustrated, unless expressly prohibited by this disclosure or the nature of the embodiments.

The phrase "configured to" means a specification or clarification of the structure or composition of an element defining what the element is, by way of a specific description of its configuration and interface with other elements or an external constraint. The phrase "adapted to" means a specification or clarification of a function or relationship of an element defining what the element does, by way of a specific description of its adaptation and interface with other elements or an external constraint. Functional language within such a specification of an element within a claim is taken to be an affirmative limitation, and not a mere intended use. Functional language or context within a claim preamble is to be considered non-limiting and outside of the claim scope, unless integrated by specific reference and inclusion by the express claim scope.

The claims hereinbelow are to be construed as excluding abstract subject matter as judicially excluded from patent protection, and the scope of all terms and phrases is to be constrained to only include that which is properly encompassed. By way of example, if a claim phrase is amenable of construction to encompass either patent eligible subject matter and patent ineligible subject matter, then the claim shall be interpreted to cover only the patent eligible subject matter. The scope of the claims shall be considered definite in accordance with the ability of a judicial or administrative court or tribunal to make this determination, regardless of any retroactive or ex post facto changes in interpretation by such court or tribunal. The various disclosure expressly provided herein, in conjunction with the incorporated references, are to be considered to encompass any combinations, permutations, and sub-combinations of the respective disclosures or portions thereof, and shall not be limited by the various exemplary combinations specifically described herein.

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What is claimed is:

1. A method of operating a vehicle, comprising:

automatically planning a motion of the vehicle with an automated motion planner P^m, which conducts a search in a motion planning domain D^m to determine and optimum motion plan comprising an action a which solves a motion planning problem specified by an initial pose x^i representing a first position and a first orientation of the vehicle, a goal pose x^g representing a second position and a second orientation of the vehicle, and a road network providing constraints on the vehicle, and produces a control signal $\langle\delta,\theta\rangle$, wherein $\delta\in\Delta$ is an acceleration and $\theta\in\Theta$ is a steering angle of control operation sets Δ and Θ, such that $\langle\delta,\theta\rangle\leftarrow P^m$ (x, x') to achieve a collision-free motion trajectory ξ connecting the initial pose x^i and the goal pose x^g taking into account the constraints on the vehicle, to incrementally advance the vehicle toward a goal, the optimum motion plan comprising action a being selected dependent on an associated utility of the incremental advance that represents a change in value, based on at least a safety of the motion trajectory with respect to an environment of operation of the vehicle, a benefit resulting from the incremental advance, and a cost of the incremental advance; and

automatically planning a task for the vehicle with an automated task planner P^t, the task comprising a sequence of the actions to advance the vehicle toward the goal, selectively dependent on an optimization of an aggregate prospective utility of the task comprising the benefit resulting from achieving the goal, the costs associated with the sequence of actions, and the safety of the sequence of actions to advance the vehicle toward the goal, wherein the planning a task comprises:

calculating a plan $p\in P$ of a set of plans P based on a task planning problem within a task planning domain by D^t, including a set of states S within a factored state space, such that each state $s\in S$ is defined by values of a fixed set of variables, the task planning problem comprising an initial state $s^{init}\in S$, a goal state $s^g\in S$, and a set of actions A, each action $a\in A$ being defined by its starting state s and resulting state s', the plan p consisting of a sequence of transitions represented as $p=\langle s_0, a_0, \ldots, s_{N-1}, a_{N-1}, s_N\rangle$, where $s_0=s^{init}$, $s^N=s^g$;

defining a utility function dependent on at least a cost function Cost(s,a,s') and a safety function Safe(s,a,s') of conducting action $\langle$s,a,s'$\rangle$ in state s; and

producing an optimal plan

$$p^* = \underset{p\in P}{\operatorname{argmin}} f(\mathrm{Cost}(\langle s, a, s'\rangle), \mathrm{Safe}(\langle s, a, s'\rangle))$$

based on the utility function.

2. The method according to claim **1**, wherein the optimum plan p* is produced based on the utility function

$$p^* = \underset{p\in P}{\operatorname{argmin}} \sum_{\langle s,a,s'\rangle\in p}\left[\mathrm{Cost}(\langle s, a, s'\rangle) + \frac{\gamma}{1+e^{Safe(\langle s,a,s'\rangle)-1}}\right],$$

where γ is a constant coefficient and $\gamma>0$.

3. The method according to claim **1**, wherein the optimum action a comprises stopping the vehicle to avoid a collision.

4. The method according to claim **1**, wherein the search is conducted directly in a two-dimensional Cartesian space such that the position and the orientation of the vehicle is uniquely represented as the pose, denoted by x and constrained by an urban road network, wherein some parts of the space are designated as free space, and remaining parts are designated as obstacles.

5. The method according to claim **4**, further comprising:

planning the motion a with the motion planner P^m comprising a path planner and a tracking planner;

calculating with the path planner in a first phase, the collision-free trajectory ξ connecting the initial pose x^i and the goal pose x^g taking into account any motion constraints on the vehicle with a minimal trajectory length;

defining with the tracking planner in a second phase, control signal $\langle\delta,\theta\rangle$ to drive the vehicle to follow the calculated collision-free trajectory ξ; and

mapping the states s with a state mapping function, f:X=f(s), into a set of feasible poses X in a continuous space as available options for the motion planner P^m, wherein availability of at least one pose $x\in X$ is assumed in each state s, such that if state s is feasible, the vehicle is in a free space of D^m, and if state S is infeasible, the vehicle is not in a free space of D^m.

6. The method according to claim **1**, further comprising:

calculating the safety level, Safe($\langle$s,a,s'$\rangle$), of a motion-level implementation of the action $\langle$s, a,s'$\rangle$, wherein the safety level enables the task planner to incorporate a road condition into a process of sequencing actions toward accomplishing complex driving tasks; and

calculating a sequence of continuous sequence of the control signal $\langle\delta,\theta\rangle$ to perform the action $\langle$s,a,s'$\rangle$, comprising the acceleration $\delta\in\Delta$ and the steering angle $\theta\in\Theta$, to drive the vehicle following the collision-free trajectory, while ensuring no collision on the road, wherein sets Δ and Θ denote an operation specification of a tracking controller to drive the vehicle to follow a collision-free trajectory,

wherein $U_s(t)\cup\Delta\times\Theta$ specifies a safe control set at time t, in which all elements, denoted by $u(t)=\langle\delta,\theta\rangle$, are safe for the vehicle to perform at time t, such that a probability of elements sampled from set $\Delta\times\Theta$ being located in the safe control set U_s represents the safety level of action ⟨s,a,s'⟩.

7. The method according to claim **1**, further comprising:

receiving an input which includes the action ⟨s,a,s'⟩, a state mapping function f, the motion planner P^m consisting of path planner and tracking controller, and a tracking controller's operation specification sets Δ and Θ;

obtaining short-period trajectories of the vehicle and surrounding vehicles, where V_i, $i\in[1, \ldots, N]$ is an ith vehicle within a sensing range of the vehicle;

iteratively:

estimating a safety between the vehicle and the surrounding vehicles V_i, where $i\in[1, \ldots, N]$, given that the vehicle is performing action ⟨s,a,s'⟩ at a motion level;

calculating a safe control set $U_i^s(t)$ that includes all safe control signals with regard to the surrounding vehicles V_i at time t;

randomly sampling M elements from a set $\Delta\times\Theta$, and calculating a probability $o_i(t)$ of the sampled elements falling in set $U_i^s(t)$;

converting a list of values of the estimation of safety $\{o_i(t)\}$ into a single value o^*_i according to

$$o_i^* = \frac{\max_{t\in T}\{o_i(t)\} + mean_{t\in 7}\{o_i(t)\}}{2};$$

and

selecting a minimum value, o^*_i, $i\in[1, \ldots, N]$, as an overall safety value, where

$$0 \le i \le \frac{(t_2 - t_2)}{\omega};$$

and

producing an output of an estimated safety value Safe(⟨s,a,s'⟩)$\in[0.0,1.0]$.

8. The method according to claim **1**, further comprising: receiving inputs:

action ⟨s,a,s'⟩,

state mapping function f,

motion planner P^m, and

control operation sets Δ and Θ;

sampling initial and goal poses $x\leftarrow f(s)$ and $x'\leftarrow f(s')$, given action ⟨s,a,s'⟩, and f;

calculating a collision-free trajectory ξ^E, using $P^m(x,x')$, where $\xi^E=x$, $\xi(t_2)=x'$, and $[t_1, t_2]$ is a horizon;

predicting a trajectory ξ_i^s for an ith surrounding vehicle V_i, where $i\in[1, \ldots, N]$, and $[t_1, t_2]$ is the horizon;

for each surrounding vehicle V_i;

calculating a safe control set $U_i^s(t)$ between the vehicle and surrounding vehicle V_i at time $t\in[t_1,t_2]$, where $U_i^s(t)\cup\Delta\times\Theta$ and

$$t = t_1 + \omega \times i,\ i \le \frac{(t_2 - t_2)}{\omega}$$

sampling M elements randomly from set $\Delta\times\Theta$ and calculating a probability $o_i(t)$ of the elements falling in set $U_i^s(t)$; and

converting a list of estimated safety values, $\{o_i(t)\}$, into a scalar value o^*_i using

$$o_i^* = \frac{\max_{t\in T}\{o_i(t)\} + mean_{t\in 7}\{o_i(t)\}}{2};$$

and

selecting a minimum value, o^*_i, $i\in[1, \ldots, N]$, as a safety value.

9. The method according to claim **1**, further comprising:

calculating both costs and safety values of the vehicle's navigation actions with the motion planner P^m to produce motion trajectories;

generating the control signal ⟨δ,θ⟩ to move the vehicle;

mapping states s to 2D coordinates in continuous spaces using a state mapping function f.

10. The method according to claim **1**, further comprising:

initializing the cost function Cost(s,a,s') and the safety function Safe(s,a,s');

estimating a safety level, μ, of action ⟨s,a,s'⟩;

updating the safety function Safe(s,a,s') using μ and the cost function Cost(s,a,s') using p*; and

calculating a new optimal plan p'.

11. The method according to claim **10**, further comprising:

calculating and executing the control signal ⟨δ,θ⟩ repeatedly until the vehicle reaches the goal pose s^g with the motion planner P^m having as an output ⟨δ,θ⟩;

initializing the cost function Cost(s,a,s') with sampled poses $x\in f(s)$: Cost (⟨s,a,s'⟩)←A* (x,x');

initializing the safety function Safe(s,a,s') with Safe(s,a,s')←1.0;

calculating the optimal task plan p using the cost function Cost(s,a,s') and the safety function Safe(s,a,s'):

p←P'(s^{init}, s^g, Cost, Safe), where p=⟨s^{init}→a_0, s_1, a_1, . . . , s^g>

until plan p is not empty:

extracting a first action of p,⟨s,a,s'⟩, and calculating a safety value μ;

updating the safety function Safe(s,a,s'): Safe(⟨∈a, s'⟨)←μ and the cost function Cost(s,a,s'):Cost (⟨s,a,s'⟩)←A*(x,x');

generating a new plan: p'←P'(s, s^g, Cost, Safe); and

if p'==p

then x'←f(s'), and while x!=x',

calling the motion planner ⟨δ,θ⟩←P^m (x, x'), executing the control signal ⟨δ,θ⟩, and updating the vehicle's current pose x;

removing a tuple ⟨s,a⟩ from plan p;

else updating current plan p←p'.

12. The method according to claim **1**, wherein the task is planned with a task planner P^t, implemented using Answer Set Programming (ASP).

13. The method according to claim **1**, wherein the environment of operation comprises surrounding vehicles, wherein the surrounding vehicles are in motion.

14. The method according to claim **1**, wherein the optimization of the aggregate prospective utility comprises minimizing with a travel distance of the vehicle while maintaining a margin of safety.

15. The method according to claim **1**,

wherein the vehicle is an autonomous vehicle, and the task comprises navigating a route, further comprising determining a safety with respect to the environment of the vehicle dependent on real-time conditions of operation,

said automatically planning the task comprising selecting motion trajectory options consistent with the task that are safe with respect to a safety threshold, wherein the action comprises a maneuver, and the selected options are responsive to a cost of the maneuver, a utility of the maneuver, and a determined safety of the maneuver;

further comprising controlling the autonomous vehicle according to the planned motion.

16. The method according to claim **1**, further comprising automatically updating the planning of motion and planning of the task in real time dependent on real-time conditions of operation of the vehicle.

17. The method according to claim **1**, wherein the safety is automatically statistically determined by the automated processor based on a predicted risk, comprising a risk of collision.

18. The method according to claim **1**,

wherein the vehicle is an autonomous vehicle,

the method further comprising:

receiving data relating to a relationship of the vehicle with respect to the environment of operation;

determining the safety of the motion trajectories comprising a motion and environment-dependent safety of the vehicle within the environment of operation dependent on the received data;

said automatically planning the task comprising continuously planning a utility-optimized route for the vehicle along a path toward the goal having execution options within the route, updated dependent on the determined motion and environment-dependent safety of the autonomous vehicle;

the utility-optimized route comprising a selection of the execution options which alter a relation of the vehicle with the environment of operation, that meet at least one safety criterion with respect to the determined motion and environment-dependent safety; and

controlling the vehicle according to the utility-optimized route and automatically planned motion, to thereby achieve safe and efficient advancement of the vehicle toward the goal.

19. A computer readable medium containing non-transitory instructions for controlling a programmable processor of an autonomous vehicle, comprising:

instructions for automatically planning a motion of the vehicle with an automated motion planner P^m, which conducts a search in a motion planning domain D^m to determine and optimum motion plan comprising an action a which solves a motion planning problem specified instructions for producing an optimal plan

$$p^* = \underset{p\in P}{\operatorname{argmin}} f(\operatorname{Cost}(\langle s, a, s'\rangle), \operatorname{Safe}(\langle s, a, s'\rangle))$$

based on the utility function.

20. A system for operating a vehicle, comprising:

a sensor configured to receive information about an environment of operation of the vehicle;

an automated motion planner P^m configured to plan a motion of the vehicle, which conducts a search in a motion planning domain D^m to determine and optimum motion plan comprising an action a which solves a motion planning problem specified by an initial pose x^i representing a first position and a first orientation of the vehicle, a goal pose x^g representing a second position and a second orientation of the vehicle, and a road network providing constraints on the vehicle, and produces a control signal $\langle\delta,\theta\rangle$, wherein $\delta\in\Delta$ is an acceleration and $\theta\in\Theta$ is a steering angle of control operation sets Δ and Θ, such that $\langle\delta,\theta\rangle\leftarrow P^m$ (x, x'), to achieve a collision-free motion trajectory ξ connecting the initial pose x^i and the goal pose x^g and taking into account the constraints on the vehicle, to incrementally advance the vehicle toward a goal, the optimum motion plan comprising action a being selected dependent on an associated utility of the incremental advance that represents a change in value, based on at least a safety of the motion trajectory with respect to an environment of operation of the vehicle, a benefit resulting from the incremental advance, and a cost of the incremental advance; and

an automated task planner P^t configured to automatically plan a task for the vehicle, the task comprising a sequence of the actions to advance the vehicle toward the goal, selectively dependent on an optimization of an aggregate prospective utility of the task comprising the benefit resulting from achieving the goal, the costs associated with the sequence of actions, and the safety of the sequence of actions to advance the vehicle toward the goal, wherein the task is planned by:

calculation of a plan $p\in P$ of a set of plans P based on a task planning problem within a task planning domain by D^t, including a set of states S within a factored state space, such that each state $s\in S$ is defined by values of a fixed set of variables, the task by an initial pose x^i representing a first position and a first orientation of the vehicle, a goal pose x^g representing a second position and a second orientation of the vehicle, and a road network providing constraints on the vehicle, and produces a control signal, $\langle\delta,\theta\rangle$, wherein $\delta\in\Delta$ A is an acceleration and $\theta\in\Theta$ is a steering angle of control operation sets Δ and Θ, such that $\langle\delta,\theta\rangle\leftarrow P^m$(x,x'), to achieve a collision-free motion trajectory ξ connecting the initial pose x^i and the goal pose x^g taking into account the constraints on the vehicle, to incrementally advance the vehicle toward a goal, the optimum motion plan comprising action a being selected dependent on an associated utility of the incremental advance that represents a change in value, based on at least a safety of the motion trajectory with respect to an environment of operation of the vehicle, a benefit resulting from the incremental advance, and a cost of the incremental advance; and

instructions for automatically planning a task for the vehicle with an automated task planner P^t, the task comprising a sequence of the actions to advance the vehicle toward the goal, selectively dependent on an optimization of an aggregate prospective utility of the task comprising the benefit resulting from achieving the goal, the costs associated with the sequence of actions, and the safety of the sequence of actions to advance the vehicle toward the goal, comprising:

instructions for calculating a plan $p \in P$ of a set of plans P based on a task planning problem within a task planning domain by D^t, including a set of states S within a factored state space, such that each state $s \in S$is defined by values of a fixed set of variables, the task planning problem comprising an initial state $s^{init} \in S$, a goal state $s^g \in S$, and a set of actions A, each action $a \in A$ being defined by its starting state s and resulting state s', the plan p consisting of a sequence of transitions represented as $p=\langle s_0, a_0, \ldots, s_{N-1}, a_{N-1}, s_N \rangle$, where $s_0=s^{init}$, $s^N=s^g$;

instructions defining a utility function dependent on at least a cost function Cost(s,a,s') and a safety function Safe(s,a,s') of conducting action $\langle s,a,s' \rangle$ in state s; and

planning problem comprising an initial state $s^{init} \in S'$, a goal state $s^g \in S$, and a set of actions A, each action $a \in A$ being defined by its starting state s and resulting state s', the plan p consisting of a sequence of transitions represented as $p=\langle s_0, a_0, \ldots, s_{N-1}, a_{N-1}, s_N \rangle$, where $s_0=s^{init}$, $s^N=s^g$;

determining an optimal plan p* according to a utility function

$$p = \langle s_0, a_0, \ldots, S_{N-1}, a_{N-1}, s_N \rangle,$$

dependent on at least a cost function Cost(s,a,s') and a safety function Safe(s,a,s') of conducting action $\langle s,a,s' \rangle$ in state s; and

an output configured to control the vehicle according to the control signal $\langle \delta,\theta \rangle$ of the planned motion.

* * * * *