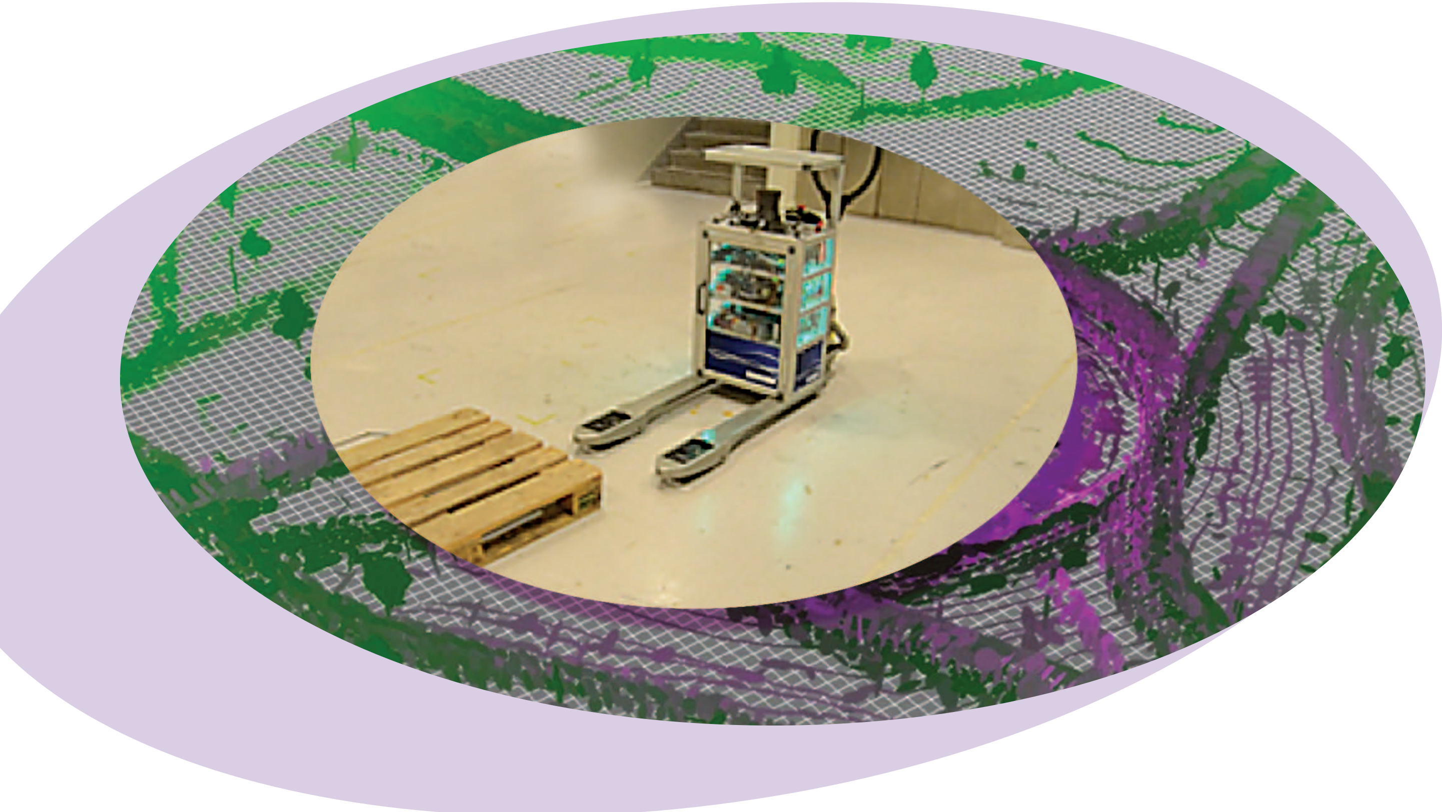
Autonomous Transport Vehicles

Where We Are and What Is Missing



By Henrik Andreasson, Abdelbaki Bouguerra, Marcello Cirillo, Dimitar Nikolaev Dimitrov, Dimiter Driankov, Lars Karlsson, Achim J. Lilienthal, Federico Pecora, Jari Pekka Saarinen, Aleksander Sherikov, and Todor Stoyanov

In this article, we address the problem of realizing a complete efficient system for automated management of fleets of autonomous ground vehicles in industrial sites. We elicit from current industrial practice and the scientific state of the art the key challenges related to autonomous transport vehicles in industrial environments and relate them to enabling techniques in perception, task allocation, motion planning, coordination, collision prediction, and control. We propose a modular approach based on least commitment, which integrates all modules through a uniform constraint-based paradigm. We describe an instantiation of this system and present a summary of the results, showing evidence of increased flexibility at the control level to adapt to contingencies.

Digital Object Identifier 10.1109/MRA.2014.2381357
Date of publication: 13 March 2015

Autonomous Transport Vehicles

Autonomous ground vehicles (AGVs) are key components in the development of flexible and efficient transport systems for logistics and industrial site management applications. Commercial solutions consisting of fleets of AGVs have been developed, e.g., for mining (Atlas-Copco mining equipment: http://www.atlascopco.com), automated material handling (Kiva Systems: http://www.kivasystems.com/), forklift automation, and industrial vehicle automation (Kollmorgen: http://www.kollmorgen.com). Although these systems are viable commercial products, they can still be improved substantially in terms of efficiency and autonomy, and many key parts of the real-world deployment phase are currently ad hoc and manual.

In this article, we describe a set of core requirements for systems comprising a fleet of AGVs. We have distilled these requirements within the ongoing project Safe Autonomous Navigation (SAUNA: aass.oru.se/Research/mro/sauna) because of a decade of cooperation with several industrial partners, including Atlas-Copco, Kollmorgen, Fotonic (www.fotonic.com), and Volvo Construction Equipment (www.volvoce.com). They point directly to a series of shortcomings in the state of the art (or to insufficient implementation of state-of-the-art results) in robot perception, motion planning, task allocation, coordination, and control.

A first set of challenges relates to the deployment phase. On one hand, the need to handcraft AGV paths for different settings should be avoided. We will refer to this challenge in the remainder of this article as *Dep1*. (Please see Table 1 for the definitions of the terms used in this article.) On the other hand, it should be possible to specify some or all AGV paths manually, albeit without committing to the particular speed at which these paths are traversed (*Dep2*). In addition, whether or not paths are specified manually, deadlocks should be avoided automatically (*Dep3*). Furthermore, perceptual functions, particularly localization, should not rely on additional infrastructure such as environmental markers (*Dep4*).

A second set of challenges is posed by the nature of the vehicles. Industrial vehicles are usually nonholonomic, which makes automatic trajectory generation a difficult task even when obstacles and coordination are not considered (referred to as *V1*). Then, the mechanical structure of the vehicles is often nontrivial (e.g., articulated vehicles and detachable trailers), thus increasing the difficulty of calculating individual motions (*V2*). The requirement to carry payloads adds extra complexity to the coordination and motion-planning problem as the size, shape, and nature of the transported goods may have an influence on the maneuvering capabilities and as the dynamics of each vehicle changes according to the weight of its load (*V3*).

Autonomous ground vehicles are key components in the development of flexible and efficient transport systems for logistics and industrial site management applications.

The key industrial requirements of efficiency and safety pose significant challenges, especially for perception. Reliable perception is negatively affected by high speeds (up to

Table 1. The definitions of the terms used in this article.

Dep1	The need to handcraft AGV paths for different settings should be avoided.
Dep2	It should be possible to specify some or all AGV paths manually, without committing to particular speeds.
Dep3	Deadlocks should be avoided automatically.
Dep4	Localization should not rely on additional infrastructure such as environmental markers.
V1	Automatic trajectory generation is difficult for nonholonomic vehicles, even when obstacles and coordination are not considered.
V2	Nontrivial mechanical structure (e.g., articulation) increases difficulty of motion planning.
V3	The size, shape, and nature of loads influences maneuvering capabilities and dynamics vehicles.
ES1	Reliable perception is negatively affected by high speeds.
ES2	Ensuring collision-free trajectories for large fleets is more difficult at high speeds.
ES3	Autonomous machines must behave similarly to human-operated ones.
ES4	Actions available to human drivers must be considered by autonomous vehicles.
Dyn1	Dynamic objects should be perceived, and their dynamics should be identified.
Dyn2	Object dynamics should also be considered for localization.
Dyn3	Planning should account for object and vehicle dynamics to improve plant efficiency.
AP1	Automated planning should occur at different levels of abstraction.
AP2	Task allocation and vehicle coordination should continuously refine existing plans in response to new requests or contingencies.
AP3	Task allocation and vehicle coordination should provide temporally/spatially flexible solutions.
AP4	Task allocation and coordination should be integrated with execution monitoring.

3,040 km/h) (called *ES1*) as is the ability to generate collision-free trajectories for large fleets (*ES2*). High speeds also impact safety when autonomous vehicles share the workspace with human-operated vehicles. This entails that the autonomous machines must behave in a way comparable with human-operated ones (*ES3*) and that the actions available to (noncontrollable) human drivers must be considered by autonomous vehicles (*ES4*).

In many deployed solutions, the dynamic nature of the environment is ignored. Fully dynamic objects (e.g., people, other vehicles, and so on) are often treated as normal obstacles, and the vehicles simply stop when encountering them. It is, therefore, important to perceive dynamic objects, identify different types of dynamics, and learn how they are spatially distributed (*Dynl*). The obtained information should also be considered for localization (*Dyn2*) and planning (*Dyn3*) to improve plant efficiency.

The current large-scale industrial deployments of AGVs rarely include more than crude heuristics to optimize, e.g., mission scheduling. Considering the efficiency and flexibility requirements and the complexity of the overall task, it is thus clear that the system must display automated planning capabilities at different levels of abstraction (AP1). Continuous task allocation and vehicle coordination should always be able to refine existing plans in response to new requests due to, e.g., changed deadlines, new goals, or newly perceived obstacles (*AP2*). To achieve robustness, task allocation and vehicle coordination should provide flexible solutions (*AP3*), e.g., sets of collision-free trajectories instead of precise temporal instants, and these reasoning tasks should be integrated with execution monitoring (*AP4*). In this way, another limitation of current industrial solutions can be circumvented, which is that the resolution of spatial conflicts is often performed offline through manually synthesized traffic rules whose correctness cannot be formally proved.

The SAUNA Approach

The SAUNA project attempts to address these requirements not in isolation but rather within an integrated approach. The approach builds upon two key principles: least commitment and modularity.

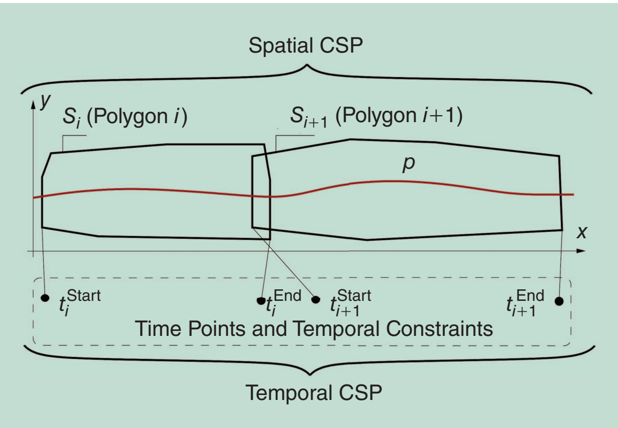


Figure 1. A trajectory envelope for a vehicle consisting of two sets of polyhedral and temporal constraints.

Least commitment means that decisions on the behaviors of vehicles in the fleet are not committed to until necessary. For instance, it may be decided that, because of an automated coordination procedure, two vehicles should not be in a particular area at the same time to avoid a possible collision. However, this decision does not result in a specific trajectory for the two vehicles; rather it is maintained as constraints on the two vehicles' trajectories. Crucially, these constraints are considered by other decision-making procedures of the integrated system, e.g., by the controllers, which synthesize the control actions that will actually displace vehicles. The advantage of least commitment is that decisions on vehicle behavior can be more informed. For instance, suppose that the specific speeds have not been committed to for vehicle trajectories, and, instead, information that excludes kinematically infeasible speeds has been computed; then, a procedure that coordinates multiple vehicles to avoid collisions may leverage the possibility to alter speeds rather than change paths. If specific paths were not committed to and a wider choice of possible paths was maintained, then collision avoidance could also decide whether to alter the speed or to alter the path to avoid a collision.

To implement least commitment, we have chosen to rely on an iterative constraint posting mechanism, whereby constraints are added to an overall constraint-based representation of vehicle trajectories. The posted constraints progressively prune out possible vehicle behaviors. For instance, perception posts spatial constraints representing the drivable area of a map, and coordination imposes constraints that prune out colliding trajectories.

The constraint-based approach directly enables modularity in that the computation and imposition of constraints is performed by dedicated modules. The overall schema does not require these modules to implement an automated procedure (addressing *Dep2*). One or more modules could indeed consist of a user interface for direct input or a pre-existing system used in the particular application domain. For instance, several industrial logistics companies employ handcrafted paths in their deployments and do not wish to deviate from this type of procedure for determining navigable paths.

The common constraint-based representation is grounded on a generalization of the notion of trajectory. A trajectory consists of a path and a temporal profile. (Throughout this article, we assume planar paths, which is consistent with the requirements of most current industrial applications.) A path is a function $\boldsymbol{p}:[0,1]\rightarrow\mathbb{R}^2\times\mathbb{S}^1$ that describes the possible positions of the reference point of a vehicle and its orientations and has a normalized domain $[0,1]$. In particular, $\boldsymbol{p}(0)$ denotes the starting pose, and $\boldsymbol{p}(1)$ denotes the final pose of the vehicle's reference point. A temporal profile $\sigma:\mathbb{R}^+\rightarrow[0,1]$ denotes the position of the reference point along the path at different points in time. Together, $\boldsymbol{p}$ (the path of the reference point) and σ (its temporal profile) define a vehicle's trajectory, i.e., $\boldsymbol{p}(\sigma(t))$.

A trajectory is said to be feasible if perfect execution in nominal conditions can be achieved in the presence of bounds on the relevant state variables of the vehicle model (e.g., the steering angle) and the obstacles in the environment. A feasible trajectory is, in other words, such that it considers a first set of important mission constraints: that motions should be kinematically feasible and should not lead to collisions with known obstacles.

A collection of constraints on a trajectory is called a *trajectory envelope*. A trajectory envelope is a set of spatiotemporal constraints on a vehicle's trajectory. It is composed of a spatial envelope and a temporal envelope. The spatial envelope can be seen as a set of n sets of polyhedral constraints $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_n\}$ on the state variables of the vehicle. An example of constraints on (x, y) is shown in Figure 1. The temporal envelope is a set of n sets of temporal constraints $\mathcal{T} = \{\mathcal{T}_1, \ldots, \mathcal{T}_n\}$, one associated to each set of spatial constraints. The temporal constraints express lower and upper bounds on the time a vehicle's reference point can be in a particular spatial polyhedron. A more formal definition of trajectory envelope is outside the scope of this article, and details can be found in [1]. For the purpose of describing the overall SAUNA approach, it is sufficient to state that a vehicle's trajectory envelope $\mathcal{E}$ is a set of spatial and temporal constraints on its reference point, i.e., $\mathcal{E} = (\mathcal{S}, \mathcal{T})$. $\mathcal{E}$ is said to be feasible if it contains at least one feasible trajectory $\boldsymbol{p}(\sigma)$.

The spatial and temporal envelopes of each vehicle constitute two constraint satisfaction problems (CSPs) [2]. A solution of the spatial CSP represents a particular choice of path $\boldsymbol{p}$ for all vehicles, while a solution of the temporal CSP represents a particular choice of temporal profile σ. Consequently, the union of the two CSPs defines the collection of all possible trajectories for all vehicles.

While the trajectory envelopes of all vehicles in a fleet may be individually feasible, the set of trajectory envelopes as a whole may not be. This is because global constraints exist, such as the admissible concurrent use of the floor space (a shared resource). All of these constraints can be seen as implicit spatial and temporal constraints. Therefore, the process of enforcing the global constraints can be reduced to that of inferring the spatial and temporal constraints entailed by the global ones and imposing them on the set of trajectory envelopes. This process yields what we call a *feasible set of trajectory envelopes*.

Overall, the SAUNA system is such that commitment increases from goal specification to coordination by means of increasingly tight constraints. This is shown in Figure 2; starting from an empty environment [Figure 2(a)], task allocation posts temporal bounds on areas to reach as a result of task allocation [Figure 2(b)], motion planning, in conjunction with perception, defines temporally sequenced sets of polyhedra that encapsulate admissible paths [Figure 2(c)], and coordination and collision prediction add constraints that disallow collisions and deadlocks [Figure 2(d)]. Controllers also avoid commitment to a specific trajectory (*Dep2*) as the spatial placement of the reference point remains bounded by constraints, and its temporal placement can be altered by selecting an alternative reference trajectory [Figure 2(e)].

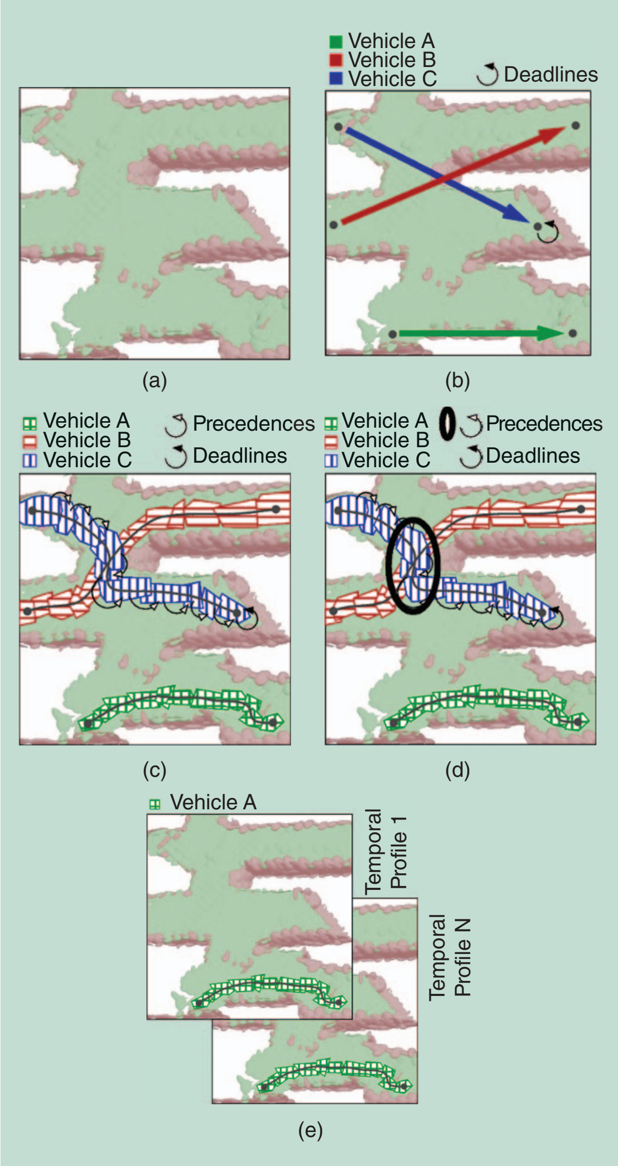


Figure 2. An increasing amount of constraints are posted by the various modules into the common constraint network. The commitment to a specific trajectory is also re-evaluated during execution as controllers have the faculty to choose among one of several precomputed reference trajectories based on tracking performance. (a) Given an example environment, (b) the task planning posts temporal bounds on areas to reach as a result of task allocation, (c) motion planning, in conjunction with perception define temporally sequenced sets of polyhedra, which encapsulate admissible paths, (d) coordination (and collision prediction) adds temporal (and spatial) constraints that disallow collisions and deadlocks, and (e) vehicle controllers follow one of a set of *N* alternative trajectories within the given spatial constraints.

The fact that every constraint, local to one vehicle or global, can be reduced to spatial and/or temporal constraints suggests a modular approach to feasibility enforcement. In particular, the refinement process, which excludes infeasible trajectories from the set of all trajectory envelopes, can be carried out by distinct modules separately, each imposing a

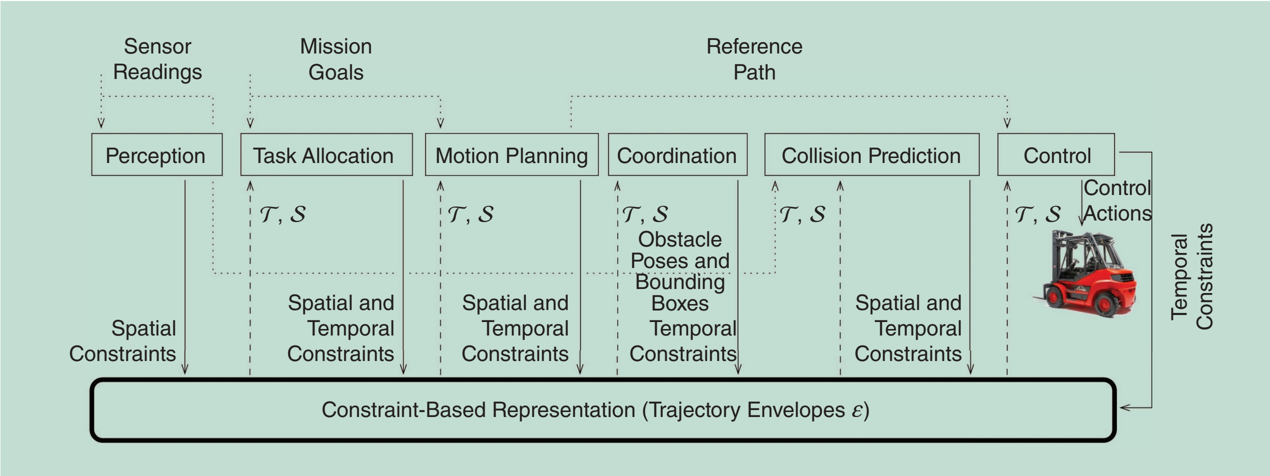


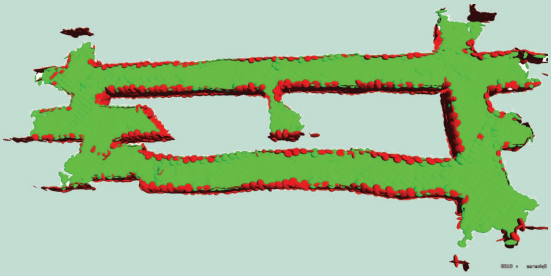
Figure 3. The SAUNA functional schema. The dashed arrows indicate information extracted by each module from the constraint-based representation, which can be either temporal envelopes ($\mathcal{T}$) or spatial envelopes ($\mathcal{S}$). The continuous arrows indicate the refinements that modules post to the overall problem, i.e., temporal and/or spatial constraints that modify the envelopes. The dotted arrows indicate the inputs and signals exchanged between modules.

particular set of constraints. In SAUNA, we have divided this collection of reasoning capabilities into six functional modules, as shown in Figure 3.

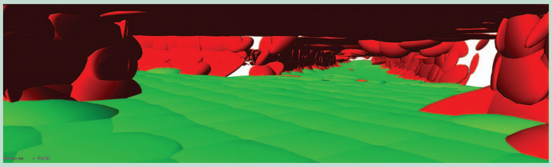
- *Perception* is responsible for constructing collections of spatial constraints, which subsume vehicles' paths, given the perceived drivable area. In addition, perception is responsible for localization and fixed/mobile obstacle tracking. Note that perception dynamically posts spatial constraints, as obstacles may become known gradually over time.
- *Task allocation* addresses mission goals and computes start-to-destination pairs of regions that vehicles should visit (given the perceived drivable area). It also posts temporal constraints stating the desired deadlines or release times (i.e., when vehicles should be in the designated areas).
- *Motion planning* uses the perceived drivable area to compute sets of spatial constraints, sequenced by temporal constraints, which identify how vehicles should displace themselves across the drivable area to achieve the constraints posted by task allocation. These sequences are trajectory envelopes containing paths that are guaranteed to be kinematically feasible.
- *Coordination* is responsible for further refining the trajectory envelopes with constraints that exclude deadlocks and collisions between controlled vehicles. The input, calculated by motion planning, is a sequence of overlapping convex polyhedra for each robot. The output consists of temporal constraints that exclude trajectories leading to vehicles being in overlapping areas during overlapping temporal intervals as well as temporal profiles that exceed the known speed limits for vehicles.
- *Collision prediction* imposes constraints that exclude collisions with vehicles that are not autonomously guided and other dynamic obstacles in the environment. It enriches the trajectory envelopes with spatial and temporal constraints, which guarantee the absence of collisions, given current perception, known trajectory envelopes for controlled vehicles, and the predicted behavior of dynamic obstacles.
- *Control* modules on board the vehicles are responsible for computing control actions for vehicles in such a way that all spatial and temporal constraints (which have been refined by the previous modules) are enforced. In addition, controllers measure the performance they achieve in following a reference trajectory. This allows them to dynamically impose further constraints that restrict the trajectories of all vehicles in the fleet to maximize the collective performance.

As shown in Figure 3, all modules reason upon the current collection of spatial and temporal constraints ($\mathcal{S}$ and $\mathcal{T}$, respectively) in the common constraint-based representation. They post specific constraints—spatial, temporal, or both—to the common constraint-based representation to refine the trajectory envelopes because of their particular inference procedures. The modules refine the representation continuously and are triggered by their inputs. Perception may refine the spatial envelopes when sensors detect changes in the environment; task planning is activated when mission goals appear or change, or when the temporal or spatial envelopes of existing trajectories are modified; motion planning recomputes polyhedra sequencing when new goals appear and/or when spatial constraints change; coordination is triggered when trajectory envelopes overlap both spatially and temporally, a condition that can exist when envelopes are first computed or when temporal constraints are added by collision prediction; the temporal and spatial envelopes, as well as newly perceived moving objects, trigger collision prediction; and control modules on board the vehicles adapt control actions in the face of new trajectories to follow. The overall result is a constraint network that represents a feasible set of trajectory envelopes for all vehicles in the fleet.

In the remainder of this article, we provide a brief overview of each module and present an instance of the entire system. The description also focuses on which of the



(a)



(b)

Figure 4. (a) The top view and (b) a detailed view of a 3-D-NDT map of an underground mine. Each Gaussian component is represented as an oriented ellipsoid scaled at 3σ levels. The color coding represents the results of a terrain traversability algorithm: green represents drivable, and red represents nontraversable space.

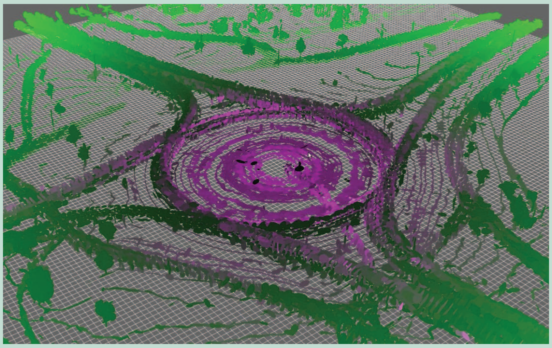
challenges shown in the "Autonomous Transport Vehicles" section are tackled and how.

Rich Three-Dimensional Perception

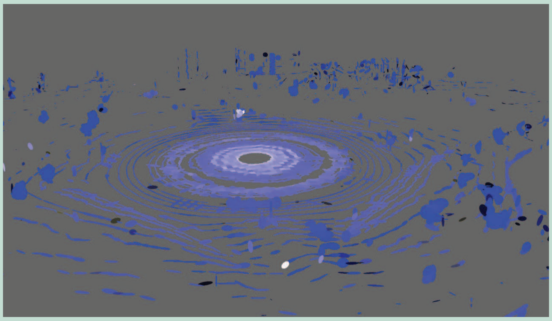
A key role of the perception system in the overall SAUNA architecture is the computation of trajectory envelopes that avoid collisions with obstacles. Extracting the safe drivable area of the environment and posting the appropriate spatial constraints is a central perception task.

Because often neither two-dimensional (2-D) nor three-dimensional (3-D) geometrical information is sufficient, it is important to consider rich 3-D perception, i.e., perception based on geometrical information combined with additional sensor data [e.g., red green blue (RGB) color, reflected light intensity, or temperature values] integrated into environment models that store occupancy together with additional dimensions (patterns of dynamic changes, for example).

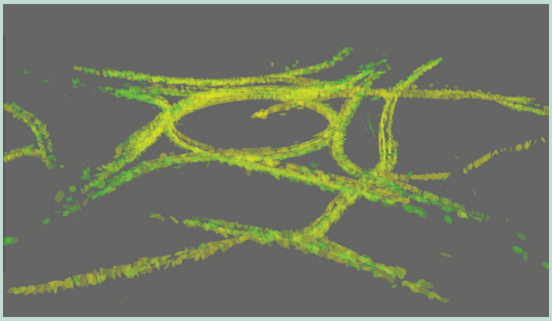
To address challenges ES1, ES2, and ES4, fast and efficient sensor processing and fusion algorithms are necessary. Given the large amount of data obtained from current 3-D and vision sensors, a compact yet accurate spatial modeling technique is vital to the performance of the perception module. The SAUNA perception system uses the 3-D-normal-distributions-transform (NDT) [3]—a fast, grid-based Gaussian mixture estimate—to represent and reason about space. The 3-D-NDT representation is accurate yet compact and, thus, is well suited to address the challenges of real-time and long-term operation in an industrial environment. An example top view of a 3-D-NDT map computed from data obtained with an actuated SICK laser range scanner is shown in Figure 4(a), while Figure 4(b) shows a detailed view of the same environment (an underground mine). This representation has been used in multiple autonomous navigation contexts, including



(a)



(b)



(c)

Figure 5. The 3-D-NDT models constructed from incremental 3-D range updates: (a) the map built without accounting for dynamics, (b) the static parts of the environment as learned by our novel algorithm, and (c) the dynamic parts of the environment can be identified and aggregated.

scan registration [3], [4], path planning [5], and loop closure [6], and has also been extended to a rich 3-D context by incorporating color information [7].

An important application of rich 3-D perception is the computation of drivable areas. The 2-D occupancy maps, traditionally used in indoor environments, offer a straightforward extraction of traversable regions but are often not informative enough to make correct decisions. A simple example of a potential failure in an industrial environment is moving a forklift truck through a door, which can result in collisions with the top of the frame if the fork has not been lowered. Conversely, reasoning about traversable regions in a 3-D-aware framework prevents collisions with the environment or dynamic entities, leading to reduced wear, tear, and accidents. The 3-D-NDT representation is readily usable for fast traversability analysis based on 3-D information alone [5], producing a reachability map (as in Figure 4), given a set of geometric and kinematic vehicle parameters. Using additional, nongeometric information available in rich 3-D perception can increase the speed and reliability of the traversability analysis and improve the computation of drivable areas.

Another set of perception-related challenges (*Dyn1* and *Dyn 2*) stems from the time scales of operation in industrial environments. Vehicles are often required to operate around the clock on ever-changing factory floors and, thus, must account for variability in the areas that are drivable. Vehicle position estimates in indoor industrial environments are often performed using static landmarks, such as reflective laser or visual beacons. This localization strategy produces accurate results but has several shortcomings, chief among which is beacon occlusion. Localization by comparing range measurements to a prerecorded map of the environment is a viable alternative (*Dep4*), promising shorter system setup times and increased robustness to dynamics and occlusions [8]. In the SAUNA system, we use 3-D range sensors to localize against a dynamically evolving rich 3-D model. The challenge thus becomes to maintain a consistent model of the environment and to learn how to distinguish static parts from dynamic ones. In addition, the different levels and types of dynamics can be identified depending on a chosen time scale. Identifying slowly changing elements, such as piles of goods to be transported in a factory automation scenario, is particularly important for localization. Failure to identify slow changes can lead to drift in localization estimates, while quickly changing portions of the environment are of interest to the traversability analysis and collision avoidance tasks. We employ 3-D-NDT maps to perform such dynamic mapping. Our approach extends the iMac representation to create independent Markov chain occupancy grid maps of dynamic environments [9] and employs a novel 3-D-NDT update algorithm [10]. The approach is shown in Figure 5, which shows a busy roundabout (the models were created by incrementally updated 3-D range data collected with a Velodyne-HDL64 laser scanner). If dynamics are not considered, an inconsistent model [Figure 5(a)] is produced. Application of our dynamic mapping approach, however, produces separate static [Figure 5(b)] and dynamic [Figure 5(c)] models of the environment.

The output of the SAUNA perception system consists of several modes of information: position estimates, drivable and obstacle areas in the map, and dynamically updated local maps. These results of the perception system are posted to the common constraint-based representation in the form of spatial constraints: 1) the drivability map is utilized to obtain a spatial envelope of safe states around a nominal trajectory and 2) the set of allowed vehicle configurations is represented as a sequence of overlapping convex polyhedra. Using convex polyhedra is particularly beneficial for the control module (see the "Control" section) as it allows for reasoning about the allowed states of the vehicle in an efficient manner.

Task Allocation

In the context of autonomous industrial vehicles, tasks are often fairly well specified, involving a number of places to be visited and a number of loads to be picked up or delivered. The decisions that the task allocation (see Figure 3) needs to make mainly concern which vehicles to allocate to each task and how to schedule the tasks. The former issue has been studied in the area of multirobot task allocation [11]. The problem of allocating tasks to industrial autonomous vehicles is characterized by some general features that span across different application domains. The positions of vehicles are important, as are the load capacities and constraints on the load types; there may also be deadlines on pickups and deliveries; the contents of an order can vary, from a simple start-goal point pair to complex programs with conditionals and loops; and orders may either be known beforehand or arrive during operation.

Presently in SAUNA, we employ a centralized task allocation system (*AP1*) that satisfies deadlines (when possible) while minimizing the total driving distance to the starting points of orders. Each vehicle can be assigned a sequence of orders, and previous assignments can be reconsidered when new orders arrive (*AP2*).

The output of the task allocator in our approach is a collection of start-goal point pairs for all vehicles (i.e., no specific path is committed to, *AP3*). The correct sequencing of tasks is ensured by temporal constraints (e.g., deadlines), which are computed and added to the constraint-based trajectory envelope representation. There might also be feedback from motion planning or coordination if those modules detect that a route is not navigable or that a deadline cannot be fulfilled (*AP2*). This feedback can be included as constraints when a new allocation is computed, e.g., a constraint stating that, at most, one vehicle can move either from A to B or from C to D during a given time interval.

Motion Planning

Many of the problems underlying automated motion planning for autonomous vehicles have been addressed in [12]. As a result, important advancements have been made in separate parts of the overall problem, e.g., in multirobot path planning, which is to date a very active research area [13], [14]. However, these approaches usually rely on unrealistic restricting assumptions, such as that the agents move on a grid [15], or lack the ability to provide important guarantees in the planned motions, e.g., not ensuring deadlock-free situations [16], [17].

The spatial envelope $\mathcal{S}$ for a fleet of vehicles can be calculated starting from an initial reference path for each vehicle. These paths, as is the case in many industrial applications [18], may be given or may be computed dynamically. In our current implementation, we employ the latter approach (*Dep1*). In particular, we use a centralized lattice-based motion planner (*AP1*) to compute optimal or highly optimized paths between destinations (where each node of the lattice represents a pose of the vehicle) [19]. The cost function is based on the distance between nodes (along the edges) of the lattice, scaled by a cost factor that penalizes backward and turning motions. These paths can be seen as an initial, very tight collection of convex polyhedra, which is then relaxed to obtain a larger spatial envelope for each vehicle.

The planner uses a set of predefined, kinematically feasible motion primitives, which are repeatedly applied to obtain a directed graph that covers the state space. The graph is then explored using A^* [20], or anytime repairing A^* (ARA^*) (an efficient anytime variant) [21], which can provide provable bounds on suboptimality. Effective heuristic functions [22], as well as offline computations for collision detection, are employed to speed up exploration of the lattice. Our approach is inspired by existing lattice-based path planners [23] that are successfully used in real-world applications. It extends existing work by providing the possibility to compute paths for multiple robots jointly. This ensures that the computed spatial envelopes provide the opportunity for vehicles to yield to others. All paths are generated such that there exists a time profile that yields feasible trajectories (V1, 2), under the assumption of car-like and waist-actuated vehicles.

Coordination

The feasibility of a set of trajectory envelopes cannot be ascertained without checking global constraints such as floor space. In particular, two trajectory envelopes (of different vehicles) that overlap in both time and space imply the possibility of a collision. The temporal and spatial overlap defines a conflict set, i.e., a set of pairs of spatial polyhedra with nonempty intersections and whose associated temporal constraints also intersect (i.e., it is possible for the vehicles' reference points to be in a common area at the same time).

Note that since trajectory envelopes constitute both a temporal and a spatial CSP, it is sufficient to eliminate solutions from these CSPs that entail the possibility of both temporal and spatial overlap. In other words, we are interested in enforcing the feasibility of the set of all trajectory envelopes for all vehicles (*AP3*). The problem of finding an overall set of trajectory envelopes that is feasible requires a significant computational overhead. Several strategies are possible, one being to refine only the spatial envelopes of spatiotemporally intersecting trajectory envelopes to eliminate the spatial overlap. Another possibility is to add temporal constraints that eliminate temporal overlap. The third option is to perform one or both refinements, depending on some particular heuristic indicating the impact of the refinement on the feasible trajectories. In SAUNA, we have explored the second option, i.e., the trajectory coordination algorithm resolves concurrent use of floor space by altering when different vehicles occupy spatially overlapping polyhedra. More precisely, the algorithm refines the temporal envelopes by adding temporal constraints $\mathcal{T}_a$. This yields a feasible set of trajectory envelopes.

Finding a set of additional constraints that make the set of trajectory envelopes feasible can itself be cast as a CSP. The variables of this CSP are conflict sets, i.e., pairs of polyhedra that intersect and whose associated temporal variables may overlap. The values of these variables are temporal constraints $\mathcal{T}_a$ that eliminate this temporal overlap. It can be shown that a solution to this CSP prunes out of the trajectory envelopes those trajectories that lead to a collision between controlled vehicles (*ES2*). In addition, the identified temporal constraints guarantee the absence of deadlocks (Dep3).

In real deployments of AGVs, it is common practice to dynamically impose deadlines on vehicles reaching their destinations (AP2). Accounting for such constraints renders the previously mentioned trajectory coordination problem NP-hard. Note also that the minimizing makespan (i.e., the total completion time of all trajectories) is equivalent to resolving the problem with increasingly tight deadlines on all vehicles and is therefore NP-hard. The (centralized) coordination algorithm proposed in SAUNA, detailed in [1], employs a powerful heuristically guided, systematic CSP search to find the resolving temporal constraints $\mathcal{T}_a$. The search employs a spatial heuristic for deciding which pair of spatiotemporally overlapping polyhedra to separate in time and a well known temporal heuristic [24] to decide which vehicle should take precedence.

The key industrial requirements of efficiency and safety pose significant challenges, especially for perception.

Collision Prediction

To address the collision prediction challenge, we focus on (noncontrollable) human-driven vehicles (*ES4*) and go beyond reactive collision-avoidance solutions to account for possible collisions before they happen. The key idea is to make vehicles proactive, i.e., able to adapt their motion as early as possible to minimize the risk of collision while still moving toward their targets. To do so, our solution uses the continuous flow of refinements to the trajectory envelopes provided by the perception and coordination modules. Each obstacle detected by perception is described by a set of probabilistic attributes that includes an oriented bounding box and color information. Such perceptual information is used to perform short-term tracking of nearby perceived moving objects, with the aim of extracting information about their motion, i.e., position and velocity. Motion information is then used to compute probabilistic estimates of the future positions of each of the tracked objects. Possible future collision with a specific object is estimated as the probability of future intersection between the bounding box of that object and the spatial envelope of a vehicle. In our current implementation, we compute the probability of intersections using sequential Monte Carlo estimation techniques [25]. For each tracked object, we create a particle filter that estimates the future positions of the object. The probability of collision is calculated as the ratio of the number of particles that result in intersections and the total number of particles for each object.

If the estimated probability of collision exceeds a predefined threshold at some time t in the near future, the temporal and spatial constraints are revised to ensure collision-free motion of the vehicle. Note that this entails a (arbitrarily) small possibility of collision. For this reason, all vehicles possess an emergency stop behavior, which relinquishes proactiveness in favor of guaranteeing safety in all situations.

Control

After coordination, trajectory envelopes contain many kinematically feasible, collision- and deadlock-free trajectories for each vehicle. A tracking controller on board each vehicle is capable of computing control actions for the vehicle given these envelopes, if the temporal profile is fixed (i.e., one solution of the temporal CSP is extracted). This fixed temporal profile, combined with a path contained in the spatial envelope, can be used to obtain a reference trajectory.

The aim of a vehicle controller is to compute control actions that follow the reference trajectory as closely as possible. In SAUNA, this computation is implemented by an embedded optimization process. Deviations from the reference trajectory that fall within the spatial constraints in the trajectory envelope are guaranteed to be deadlock and collision free, both with respect to the other controlled vehicles and static obstacles. In addition, they will not lead to collisions with other human-driven vehicles, as collision prediction has refined the spatial and temporal envelopes to reflect the predicted motion of the human drivers.

The embedded optimization schema assumes that a specific temporal profile is used. On one hand, this implies a restriction on how the controller compensates for deviations: only through spatial adjustments. On the other hand, the temporal commitment implies that the control problem can be formulated in such a way that it is easily solvable. The temporal commitment means that the controller is bound by a fixed schedule, i.e., control actions must lead the vehicle to enter and exit polyhedra at specific times. However, a deviation from the path could require a compensation that leads to unacceptable accelerations (e.g., because the vehicle is carrying a heavy load), therefore making it undesirable to respect the schedule. In SAUNA, we have developed [1] a schema that relies on precomputing multiple alternative temporal profiles. These alternatives can be selected according to the tracking performance: all have the same spatial envelopes but different fixed temporal profiles, thus leading to alternative reference trajectories.

The embedded optimization approach used here is known as model predictive control (MPC) because control actions are computed considering the kinematic model of the vehicle. MPC is one of the most successful embedded optimization schemes and has been used in a wide variety of industrial applications [26]. The application of MPC in the context of tracking a reference trajectory using a nonholonomic vehicle has been discussed by several authors, e.g., [27]. In our work, the fact that spatial constraints are convex polyhedral makes it possible to compute control actions in the millisecond (or even microsecond) range. Therefore, it is possible within one sampling time to compute control actions for several alternative reference trajectories and choose the one that provides the best tracking performance.

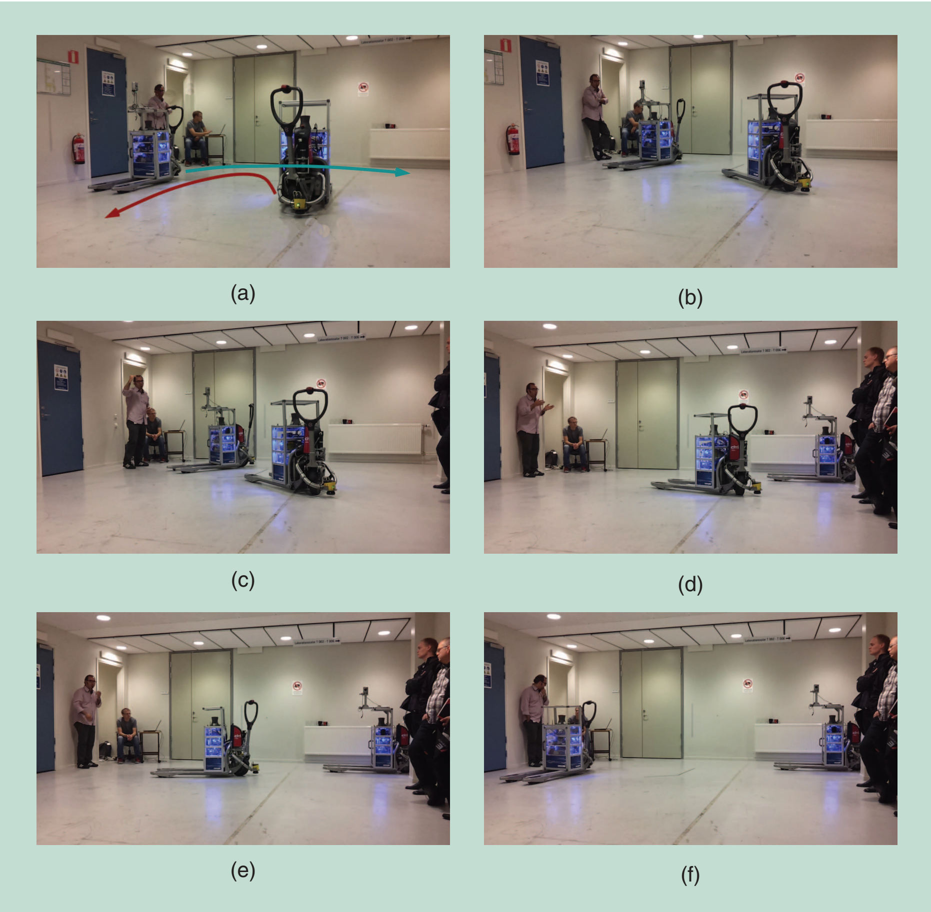


Figure 6. The first scenario: (a) vehicles 1 and 2 and their targets, (b) vehicle 1 is braked, causing vehicle 2 to yield, (c) the brake is released and vehicle 1 resumes motion, (d) vehicle 2 resumes motion, and (e) vehicle 1 and (f) vehicle 2 reach their final poses. (Photos courtesy of Ola B. Pettersson.)

During execution, controllers write to the common representation their current state of execution. This information is modeled as temporal constraints on polyhedra. These constraints update the time in which vehicles will reach polyhedra further along in their missions, hence refining the temporal profile of all vehicles. Consequently, a delay of a vehicle will be propagated to the temporal profiles of all other vehicles; this, in turn, may require recoordination or a change in task allocation. Further details on this approach to execution monitoring (*AP4*) are reported in [28].

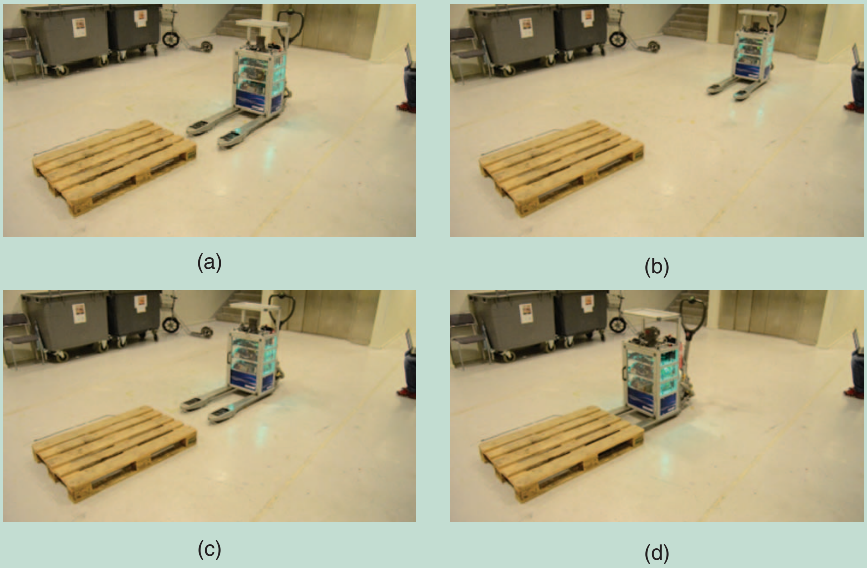


Figure 7. The second scenario: (a) a vehicle reaches the loading zone and observes the pose of the pallet, (b) the observed pose requires the vehicle to realign, and (c) the vehicle has realigned and (d) commences the pickup operation. (Photo courtesy of Henrik Andraesson.)

Toward an Integrated System

An instantiation of the SAUNA approach with specific automated reasoning modules has been realized in the robot operating system (ROS) framework. Communication among modules is achieved through ROS topics and specialized ROS message formats.

Evaluation of the approach has focused on both individual modules and on the entire system. Two of the most computationally challenging subproblems of the overall fleet management problem are motion planning and coordination: 1) the former must solve a graph search problem that is exponential already for one vehicle and 2) the latter also has exponential worst case complexity if deadlines are included in $\mathcal{T}$. Despite the high complexity, we have shown [1] that lattice-based motion planning, coupled with constraint-based vehicle coordination, renders these individual problems practically feasible in realistically sized environments.

Several evaluations have been performed to validate the overall SAUNA system in terms of practical usability and suitability for realistic scenarios. For the former, we have employed two Linde forklift platforms. One of the test scenarios involved repeatedly posting goal poses for the two forklifts. The limited space in the test environment leads to significant spatiotemporal overlap, thus incurring frequent yielding behavior. These vehicles are shown executing a coordinated maneuver when an unforeseen contingency is created by sending vehicle 1 a brake command [Figure 6(b)], causing vehicle 2 to yield. When the brake command is retracted and vehicle 1 moves out of vehicle 2's path, vehicle 2 resumes navigation. This behavior is because the coordinator and the two controllers all read from and write to the common representation, thus ensuring collision-free motions. (Videos of the scenarios described here are available at http://aass.oru. se/~ fpa/ SAUNA- movies.)

A second scenario is shown in Figure 7, which shows the continuous refinement of the common representation because of perception. In particular, the vehicle's task is to pick a pallet whose position is only roughly known. When the vehicle reaches the area [Figure 7(a)], its onboard RGB depth sensor re-estimates the pose of the pallet. To achieve

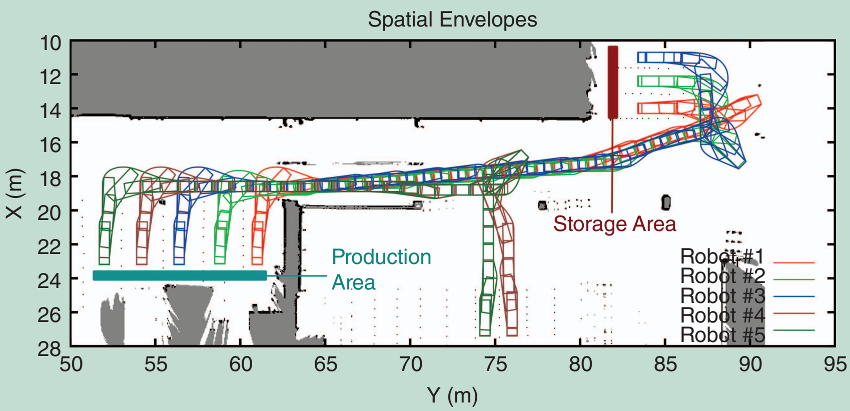


Figure 8. The spatial envelopes generated for five forklifts in a realistic industrial production site.

the necessarily precise alignment between the vehicle and the pallet, a new goal pose is added to the common representation, which in turn leads the motion planner, coordinator, and all other involved modules to reposition the vehicle appropriately. (Videos of the scenarios described here are available at http://aass.oru. se/~ fpa/SAUNA- movies.)

To evaluate the performance of the entire system in a realistically sized scenario, we performed a set of runs in a simulated industrial production site (using a physical simulation in Gazebo). The runs involved one to five vehicles in an area that affords long motions. The layout used in the simulation is part of an actual factory in which automatically guided vehicles transit along predefined paths (see Figure 8). The vehicles were required to transport goods between the production and storage areas. Our analysis shows that the vehicle idle time never exceeded 30%, even with five vehicles and under the assumption that the motion planning and coordination are triggered only when previous goals are reached. This extremely unsophisticated form of task dispatching represents a worst case as it forces vehicles to enter an idle state while new envelopes are computed and is far less advanced than current industrial practice.

Current large-scale industrial deployments of AGVs rarely include more than crude heuristics to optimize, e.g., mission scheduling.

Formal Properties

All modules in the SAUNA system share a common formal representation. This allows to state useful formal properties of the approach. Two of these are: 1) *soundness*, i.e., whether trajectory envelopes are guaranteed to contain only kinematically feasible and collision- and deadlock-free trajectories and 2) *completeness*, i.e., whether the approach guarantees finding such trajectories if they exist. It has been shown that the SAUNA system is both sound and complete under reasonable assumptions regarding the discretization of working space and resolution of the motion primitives used by the motion planner [28]. By contrast, in most current approaches (including those used in industrial practice), it is not possible to formally guarantee the absence of deadlocks, and collision avoidance does not account for the other constraints in the system (e.g., deadlines may be unnecessarily missed as a result of local trajectory adjustments).

Discussion and Future Work

We have proposed a general, modular functional schema designed to be used in different application scenarios. Modularity is motivated by the fact that different real-world applications require different levels of automation. In particular, individual functionalities (task planning/vehicle allocation, motion planning, perception, control, and so on) are often already provided through proprietary tools that companies do not wish to replace. The SAUNA approach enables the exclusion of one or more modules by establishing a common constraint-based model that represents constraints on trajectories rather than committing to specific trajectories. The use of spatial and temporal constraints in the shared representation provides an intuitive language with which custom user interfaces can interact with the fleet. An operator can therefore easily substitute or complement the decision process of an automated procedure without disrupting automated fleet management.

It is worth commenting on the centralized nature of the SAUNA system. This facilitates maintaining a shared representation, which in turn provides the benefit of upholding formal properties and ease of integration of new modules. However, it also poses a hindrance when it comes to scalability—going beyond tens of vehicles in the current setup is not computationally feasible. For this reason, we will investigate in the near future possible ways to decentralize the approach while still maintaining the desirable features obtained so far. Good starting points for doing so are the many related results in the field of multiagent systems. These include protocols for distributed task allocation, such as contract net [29], decentralized hash tables [30] and auction-based methods [31], decentralized coordination techniques [32], and distributed algorithms for safe navigation [33].

Future work in SAUNA will address the primary issue of realizing a complete deployment using industrial vehicles in a controlled environment. In addition, to verify the claim that the SAUNA approach facilitates selective module deployment, we will focus on deploying the system in two industrial application scenarios: an automated milk production factory and an underground mine site in Sweden. These applications require the integration of different legacy modules and different levels of involvement of human operators. We also plan to make the current implementation of the SAUNA system and of its modules available as open-source ROS packages.

In the longer term, we aim to study specific techniques for addressing the remaining challenges not addressed so far, specifically, *V3*, *ES3*, and *Dyn3*. A further challenge that will be addressed is the integration of meaningful optimization strategies for particular applications (e.g., throughput of goods through a warehouse).

References

[1] F. Pecora, M. Cirillo, and D. Dimitrov, "On mission-dependent coordination of multiple vehicles under spatial and temporal constraints," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2012, pp. 5262–5269.

[2] E. Tsang, *Foundations of Constraint Satisfaction*. San Diego, CA: Academic Press, 1993.

[3] M. Magnusson, T. Duckett, and A. J. Lilienthal, "3D scan registration for autonomous mining vehicles," *J. Field Robot.*, vol. 24, no. 10, pp. 803–827, Oct. 2007.

[4] T. Stoyanov, M. Magnusson, H. Andreasson, and A. J. Lilienthal, "Fast and accurate scan registration through minimization of the distance between compact 3D NDT representations," *Int. J. Robot. Res., Special Issue 3D Exploration, Mapping, Surveillance*, vol. 31, no. 12, pp. 1377–1393, 2012.

[5] T. Stoyanov, M. Magnusson, H. Andreasson, and A. J. Lilienthal, "Path planning in 3D environments using the normal distributions transform," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2010, pp. 3263–3268.

[6] M. Magnusson, H. Andreasson, A. Nüchter, and A. J. Lilienthal, "Automatic appearance-based loop detection from 3D laser data using the normal distributions transform," *J. Field Robot.*, vol. 26, nos. 11–12, pp. 892–914, Nov. 2009.

[7] B. Huhle, M. Magnusson, W. Straßer, and A. J. Lilienthal, "Registration of colored 3D point clouds with a kernel-based extension to the normal distributions transform," in *Proc. IEEE Int. Conf. Robotics Automation*, 2008, pp. 4025–4030.

[8] J. Saarinen, H. Andreasson, T. Stoyanov, and A. J. Lilienthal, "Normal distributions transform Monte-Carlo localization (NDT-MCL)," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2013, pp. 382–389.

[9] J. Saarinen, H. Andreasson, and A. J. Lilienthal, "Independent Markov chain occupancy grid maps for representation of dynamic environments," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2012, pp. 3489–3495.

[10] J. P. Saarinen, H. Andreasson, T. Stoyanov, and A. J. Lilienthal, "3D normal distributions transform occupancy maps: An efficient representation for mapping in dynamic environments," *Int. J. Robot. Res.*, vol. 32, no. 14, pp. 1627–1644, 2013.

[11] B. P. Gerkey and M. J. Mataric, "A formal analysis and taxonomy of task allocation in multi-robot systems," *Int. J. Robot. Res.*, vol. 23, no. 9, pp. 939–954, 2004.

[12] S. M. LaValle, "Motion planning: The essentials," *IEEE Robot. Automat. Society Mag.*, vol. 18, no. 1, pp. 79–89, 2011.

[13] G. Wagner and H. Choset, "M*: A complete multirobot path planning algorithm with performance bounds," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2011, pp. 3260–3267.

[14] R. Luna and K. E. Bekris, "Push and swap: Fast cooperative path-finding with completeness guarantees," in *Proc. 22nd Int. Joint Conf. Artificial Intelligence*, 2011, pp. 294–300.

[15] A. Kleiner, D. Sun, and D. Meyer-Delius, "ARMO: Adaptive road map optimization for large robot teams," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2011, pp. 3276–3282.

[16] A. W. ter Mors, "Conflict-free route planning in dynamic environments," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2011, pp. 2166–2171.

[17] V. Desaraju and J. How, "Decentralized path planning for multi-agent teams in complex environments using rapidly-exploring random trees," in *Proc. IEEE Int. Conf. Robotics Automation*, 2011, pp. 385–403.

[18] J. Larsson, "Unmanned operation of load-haul-dump vehicles in mining environments," Ph.D. dissertation, Örebro Univ., School Sci. Technol., 2011.

[19] M. Cirillo, T. Uras, and S. Koenig, "A lattice-based approach to multirobot motion planning for non-holonomic vehicles," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, Chicago, IL, 2014, pp. 232–239.

[20] P. Hart, N. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Trans. Syst. Sci. Cybern.*, vol. 4, no. 2, pp. 100–107, 1968.

[21] M. Likhachev, G. Gordon, and S. Thrun, "ARA*: Anytime A* with provable bounds on sub-optimality," *Adv. Neural Inform. Processing Syst.*, vol. 16, pp. 767–774, 2003.

[22] R. A. Knepper and A. Kelly, "High performance state lattice planning using heuristic look-up tables," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, 2006, pp. 3375–3380.

[23] M. Pivtoraiko, R. A. Knepper, and A. Kelly, "Differentially constrained mobile robot motion planning in state lattices," *J. Field Robot.*, vol. 26, no. 3, pp. 308–333, 2009.

[24] A. Cesta, A. Oddi, and S. F. Smith, "A constraint-based method for project scheduling with time windows," *J. Heuristics*, vol. 8, no. 1, pp. 109–136, Jan. 2002.

[25] A. Doucet, N. De Freitas, and N. Gordon, Eds., *Sequential Monte Carlo Methods in Practice* (Statistics for Engineering and Information Science). Berlin Heidelberg, Germany: Springer Verlag, June 2001.

[26] S. Qin and T. Badgwell, "A survey of industrial model predictive control technology," *Control Eng. Practice*, vol. 11, no. 7, pp. 733–764, 2003.

[27] D. Gu and H. Hu, "Receding horizon tracking control of wheeled mobile robots," *IEEE Trans. Control Syst. Technol.*, vol. 14, no. 4, pp. 743–749, 2006.

[28] M. Cirillo, F. Pecora, H. Andreasson, T. Uras, and S. Koenig, "Integrated motion planning and coordination for industrial vehicles," in *Proc. 24th Int. Conf. Automated Planning Scheduling*, Portsmouth, NH, 2014, pp. 463–471.

[29] R. G. Smith. (1980, Dec.). The contract net protocol: High-level communication and control in a distributed problem solver. *IEEE Trans. Comput.* [Online]. *29(12)*, pp. 1104–1113. Available: http://dx.doi.org/10.1109/TC.1980.1675516

[30] D. Sun, A. Kleiner, and C. Schindelhauer, "Decentralized hash tables for mobile robot teams solving intra-logistics tasks," in *Proc. 9th Int. Conf. Autonomous Agents Multiagent Systems*, 2010, pp. 923–930.

[31] S. Koenig, P. Keskinocak, and C. A. Tovey, "Progress on agent coordination with cooperative auctions," in *Proc. AAAI Conf. Artificial Intelligence*, 2010, pp. 1713–1717.

[32] B. Faltings, "Distributed constraint programming," in *Handbook of Constraint Programming*, F. Rossi, P. van Beek, and T. Walsh, Eds. New York: Elsevier, 2006, pp. 699–729.

[33] K. E. Bekris, D. K. Grady, M. Moll, and L. E. Kavraki, "Safe distributed motion coordination for second-order systems with different planning cycles," *Int. J. Robot. Res.*, vol. 31, no. 2, pp. 129–150, 2012.

Henrik Andreasson, Örebro University, Sweden. E-mail: henrik.andreasson@oru.se.

Abdelbaki Bouguerra, Örebro University, Sweden. E-mail: abdelbaki.bouguerra@oru.se.

Marcello Cirillo, Örebro University, Sweden. E-mail: marcello.cirillo@oru.se.

Dimitar Nikolaev Dimitrov, INRIA, Grenoble, Meylan, France. E-mail: mail@drdv.net.

Dimiter Driankov, Oerebro University, Sweden. E-mail: dimiter.driankov@tech.oru.se.

Lars Karlsson, Örebro University, Sweden. E-mail: lars.karlsson@oru.se.

Achim J. Lilienthal, Örebro University, Sweden. E-mail: achim.lilienthal@oru.se.

Federico Pecora, Örebro University, Sweden. E-mail: federico.pecora@oru.se; federico.pecora@gmail.com.

Jari Pekka Saarinen, Aalto University, Finland. E-mail: jari.saarinen@oru.se; jari.p.saarinen@gmail.com.

Aleksander Sherikov, Centre de Recherche Grenoble, Rhône-Alpes, France. E-mail: asherikov@yandex.com.

Todor Stoyanov, Center for Applied Autonomous Sensor Systems, Orebro University, Sweden. E-mail: todor.stoyanov@oru.se.