The PAN-Robots Project

Advanced Automated Guided Vehicle Systems for Industrial Logistics

By Lorenzo Sabattini, Mika Aikio, Patric Beinschob, Markus Boehning, Elena Cardarelli, Valerio Digani, Annette Krengel, Massimiliano Magnani, Szilard Mandici, Fabio Oleari, Christoph Reinke, Davide Ronzoni, Christian Stimming, Robert Varga, Andrei Vatavu, Sergi Castells Lopez, Cesare Fantuzzi, Aki Mäyrä, Sergiu Nedevschi, Cristian Secchi, and Kay Fuerstenberg

In modern manufacturing plants, automation is widely adopted in the production phases, which leads to a high level of productivity and efficiency. However, the same level of automation is generally not achieved in logistics, typically performed by human operators and manually driven vehicles. In fact, even though automated guided vehicles (AGVs) have been used for a few decades for goods transportation in industrial environments [1], they do not yet represent a widespread solution and are typically applied only in specific scenarios.

A remarkable example is the Amazon Robotics system [2], in which AGVs are utilized for logistics in e-commerce warehouses. While this solution is very effective for this kind of application, it is worth noting that it can not be directly applied to material handling in generic factories. What makes this system unique is that the AGVs move in a constrained environment, where other entities are not allowed [3]. This makes the system not applicable to mixed environments shared by human operators, manually driven vehicles, and AGVs (Figure 1).

In this article, we present the main technological developments achieved during the Plug and Navigate (PAN)-Robots project (http://www.pan-robots.eu), which aimed at increasing the autonomy and efficiency of AGVs used for industrial logistics in environments shared with human operators. The main contribution of this article is to provide a system-level overview of those achievements, demonstrating how they can contribute in increasing the applicability of AGV systems.

Digital Object Identifier 10.1109/MRA.2017.2700325
Date of publication: 10 November 2017

Scenario and Related Works

In this article, we consider AGV systems used for transporting pallets of goods in automated warehouses, as shown in Figure 2. Specifically, we focus on common manufacturing plants characterized by large production batches, such as

 1070-9932/17©2017IEEE

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

beverage companies. Typically, in these environments, a few tens of vehicles are utilized for goods transportation (from the production machines to the warehouse, within the warehouse itself, or to the shipment area). While traditional installations consist of manually driven forklifts, advanced solutions based on AGVs are becoming increasingly popular [4].

In these applications, AGVs share the environment with other entities, such as pedestrians (i.e., human operators) and manually driven vehicles (e.g., forklifts) [5], [6]. As a consequence, safety concerns are of paramount importance; the environment is populated with dynamic entities, and avoidance of collision needs to be guaranteed. A typical solution for achieving this objective is in the use of safety laser scanners [7], which allow each AGV to detect the presence of obstacles in its vicinity and opportunely stop to avoid collisions or replan the path to be traveled [8]. As discussed in [9], safety laser scanners do not allow AGVs to classify detected obstacles and, subsequently, to make high-level decisions, such as stopping in the presence of a human (whose behavior is unpredictable) and circumventing a box (which does not move).

Computer-vision-based techniques for dynamic obstacle detection have been extensively studied in the last few years, particularly in the context of autonomous vehicles [10], [11]. Because the environment is populated by human operators, illumination is always needed. Hence, techniques based on computer vision can be effectively utilized.

Industrial environments are typically very congested; as shown in Figures 1 and 2, AGVs move through corridors and racks to collect and deliver pallets of goods. To effectively plan the motion of the AGVs and react to unpredictable events (e.g., the presence of a pedestrian) in the correct manner, multiple viewpoints as well as a global view of the environment are necessary. A sensing system was introduced in the PAN-Robots project that exploits a composition of onboard and offboard sensing systems to acquire data from the environment that are then gathered in a centralized data fusion system (see the “Advanced Sensing System” section).

The motion of the AGVs then needs to be coordinated through the environment in such a way that the requested missions (i.e., transportation of a pallet of goods from one location to another) are fulfilled. Generally, two different philosophies can be followed to coordinate the motion of the AGVs: decentralized and centralized. In decentralized coordination strategies, each vehicle defines its own path independently, based on locally available information. Coordination among vehicles is then handled locally. While those strategies are known to scale well for large-scale fleets [12], [13], they typically do not provide a complete solution. Hence, efficiency cannot always be guaranteed. Since, in industrial applications, the overall efficiency is paramount [4], we consider a centralized coordination strategy that also incorporates information acquired by the centralized data fusion system. As is typically done in industrial applications, the proposed coordination strategy considers the AGVs constrained to move along a road map [14], which is a set of (virtual) paths that let

(a)

(b)

Figure 1. (a) and (b) AGVs sharing the environment with human operators.

Figure 2. AGVs moving goods in a modern factory warehouse with high production volumes.

the AGVs reach any location of interest in the environment. Localization of the AGVs is typically managed by means of laser scanners mounted on top of the vehicles themselves, which are used to localize the vehicle with respect to a map of the environment known a priori [15].

Advanced Sensing System

The advanced sensing system proposed in the PAN-Robots project is composed of sensors installed both onboard the AGVs and in the infrastructure, as summarized in Figure 3. A centralized data fusion module is then in charge of gathering all the acquired information. We describe these modules in detail in the following sections.

Onboard Sensing System

Omnidirectional Stereo Camera and Two-Dimensional Safety Laser Scanners

The main goal of the onboard system composed of the omnidirectional stereo camera and the two-dimensional (2-D)

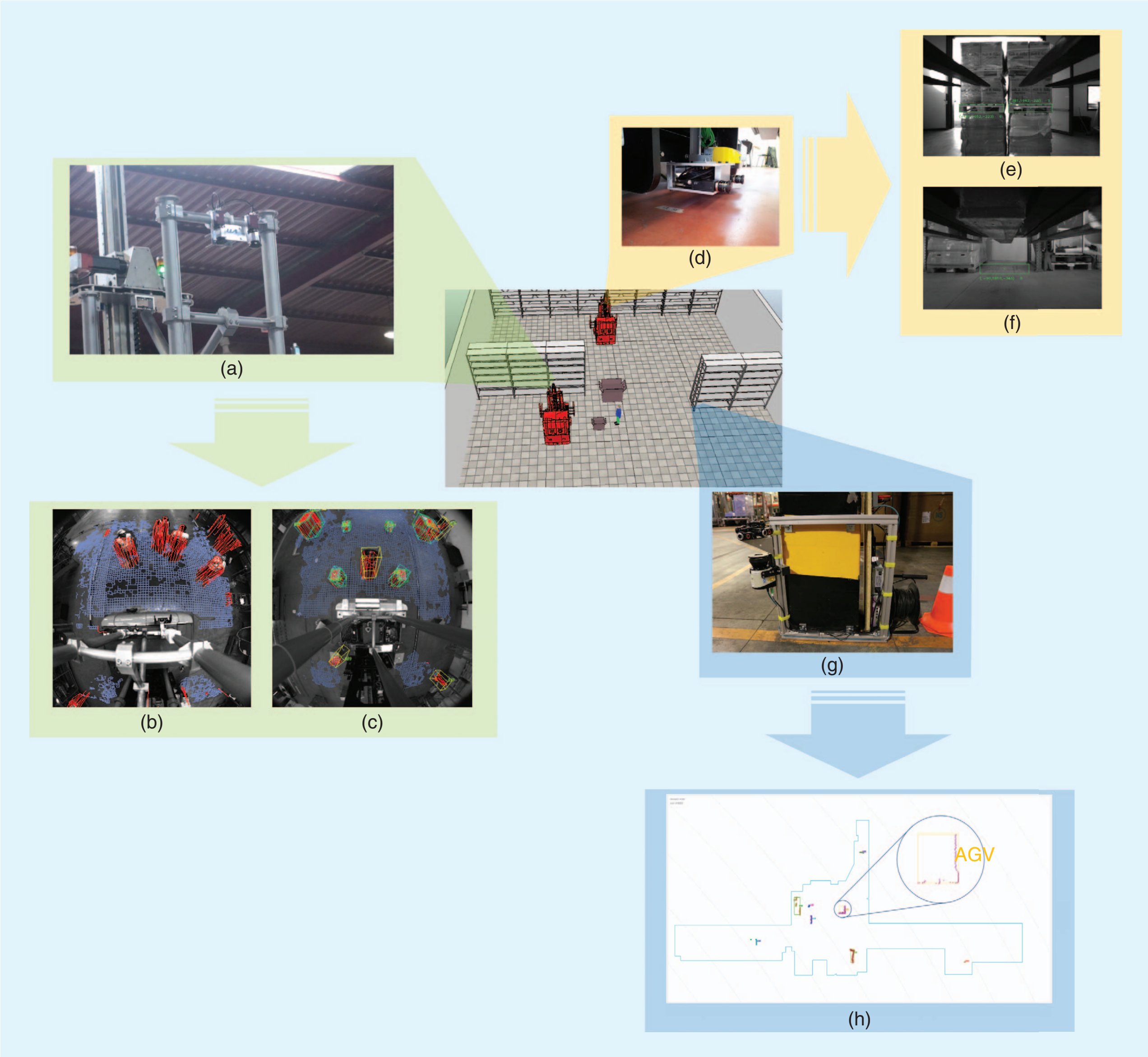

Figure 3. The sensing system developed within PAN-Robots is composed of several modules. (a) An omnidirectional stereo camera is mounted above the AGV with the purpose of providing information regarding the objects around the AGV itself. (b) In particular, an elevation map is extracted and, after data fusion with information gathered by the safety laser scanners, (c) objects are classified and tracked. (d) A stereo camera mounted under the AGV forks is utilized for load handling. In particular, it allows (e) detecting pallets during picking operations and (f) unloading cuboids for dropping operations. (g) Infrastructure laser scanners mounted on pillars (h) allow detecting, tracking, and classifying objects.

safety laser scanners is that of providing three-dimensional (3-D) surrounding perception, including object detection, tracking, classification, and environment representation. An enhanced onboard perception is provided by fusing the omnidirectional stereo 3-D data with the 2-D safety laser scanners' information. In particular, one of the key features is represented by the detection of protruding and hanging objects.

To provide information about the surroundings of the AGV, the omnidirectional stereo camera is mounted at a height of approximately 4 m on a pole. Having a vertical field of view of approximately 150°, the camera can detect objects of a height of 1 m at a distance of around 10 m. The hardware architecture of the omnidirectional stereo-vision system, as detailed in [16], consists of a pair of customized fisheye lenses, two high-resolution digital cameras, and a data-processing unit. The most important components of the data-processing unit are the actual custom 3-D vision engine control unit, which does the processing, and the NVIDIA graphics processing unit (GPU). The GPU's role is to provide real-time dense stereo reconstruction and elevation map computation.

After obtaining the camera position and parameters using intrinsic and extrinsic calibration, a multichannel rectification is performed, and the fisheye images are split in three different channels. The stereo matching and reconstruction algorithms are run on each pair of images, and the 3-D reconstructed points are obtained. To reduce the amount of data to be processed and filter the noise from the raw stereo data, an intermediate representation is built in the form of digital elevation maps (DEMs). A DEM is a 2-D Cartesian grid map in which each cell contains the corresponding height information. DEMs provide both representation flexibility and compactness and are especially useful in unstructured environments. They also provide explicit connectivity information among cells. Each cell in the DEM is classified as corresponding to the road or an obstacle based on the height information in that cell [see Figure 3(f)]. Groups of DEM cells containing points above the drivable area are labeled as obstacle cells. The neighboring obstacle cells are grouped, and, if they form a considerable area, an obstacle is detected. The obstacle is represented by a bounding box with certain dimensions and orientation. The obstacles are tracked and finally classified [see Figure 3(g)], utilizing the methodology described in detail in [17].

The laser scanners gather a range profile (scan) of the environment. As four scanners are placed around the AGV to have different fields of view in all directions, the complete environment can be observed by fusing all four range profiles of the scanners. The map of the warehouse environment, known a priori, is combined with the localization results to identify and extract regions of interest for object detection. Detected objects are tracked and classified. The data resulting from the two threads of 2-D perception and 3-D omnidirectional vision are fused onboard the AGV by a probabilistic object-level fusion approach. The sensor data fusion (described in detail in [18]) between the stereo-vision sensor findings and the laser scanner data provides high values of robustness and accuracy for detection, tracking, and classification.

The performance of the perception system was evaluated using data acquired in real industrial environments. The first experiment consisted in having a static object (in particular, a pallet of goods) on the ground detected from a moving AGV. More than 700 measurements were taken. In each configuration, the ground truth relative position between the AGV and the object was measured by means of laser scanners. It is worth noting that, due to the motion of the AGV, a relative velocity of the object could be observed as well. Table 1 summarizes the achieved results, which show very good precision of the tracked measurements. Values are shown in terms of root-mean-square error (rmse) and maximum error.

Table 1. The tracking of a static obstacle from a moving AGV: 787 measurements.

Parameter	rmse	Maximum Error
Position error	0.02 m	0.07 m
Velocity error	0.13 m/s	0.68 m/s

Another experiment consisted in having a second AGV (target AGV), moving at a known velocity and orientation, that was then measured from the first AGV. The experiment was run for five hours, using three levels of velocity and orientation. As summarized in Table 2, in all the considered cases, the rmse was less than 0.5 m/s for the velocity and less than 15° for the orientation.

Classification performance was then assessed acquiring 32 sequences, each lasting 5 min, that included three classes of obstacles: pedestrians, AGVs, and other obstacles. Sequences were manually annotated to obtain a ground truth. The system was then able to correctly classify the obstacles in more than 90% of the cases.

Pallet Loading

A fully automated AGV requires sensors dedicated to load-handling operations. For this purpose, we implemented a machine-vision-based approach that employs both intensity information and stereo depth information from two cameras mounted near the AGV forks. Stereo cameras are easy to install and require only a calibration procedure at installation time. Cameras provide a 3-D view of the scene in front of the AGV. Analysis of this allows us to perform pallet detection with localization and free space detection for unloading operations.

As shown in [19], pallet detection is achieved by applying a sliding window detection method. Relevant candidates are selected from the region of interest by analyzing the edges found in the input images. Discriminative features are then calculated for each candidate. These features are specifically designed to be invariant to gain changes to enable precise localization and to help discriminate pallets from other objects.

Table 2. The measurement of velocity and orientation of a target AGV.

		Target AGVs Orientation		
Target AGV Velocity	Parameter	0°	90°	135°
0.75 m/s	Velocity rmse	0.25 m/s	0.31 m/s	0.14 m/s
0.75 m/s	Orientation rmse	2.90°	7.14°	11.44°
1.2 m/s	Velocity rmse	0.21 m/s	0.18 m/s	0.15 m/s
1.2 m/s	Orientation rmse	1.77°	10.86°	10.42°
1.8 m/s	Velocity rmse	0.33 m/s	0.19 m/s	0.22 m/s
1.8 m/s	Orientation rmse	1.87°	4.87°	3.73°

Table 3. The performance of the pallet loading sensing system.

Parameter	Value
Detection accuracy	99%
Distance error (rmse)	6.3 mm
Orientation error (rmse)	0.5°

Table 4. The performance of the infrastructure sensing system: 1,039 measurements.

Parameter	rmse	Maximum Error
Position error	0.09 m	0.34 m
Velocity error	0.22 m/s	0.31 m/s
Orientation error	3.2°	6.2°

Figure 3 shows the results of the proposed approach. In particular, Figure 3(d) shows the detection of a pallet that allows the AGV to perform a picking operation. Conversely, Figure 3(e) depicts the unloading of a cuboid, which allows the AGV to perform a dropping operation. The accuracy of the system was assessed on a data set of 7,000 images taken in a real warehouse. Results are summarized in Table 3 and confirm that the proposed system is able to provide sufficient precision for performing pallet-handling operations.

Infrastructure-Based Environment Perception System

At warehouse black spots, such as intersections, where objects are not detectable by the AGV's onboard safety laser scanners due to the occluded field of view, special care has to be taken to avoid accidents with dynamic objects, such as pedestrians. A simple solution for workers approaching an intersection is a hemispherical mirror mounted above the intersection, which allows looking for oncoming traffic in the remaining arms of the intersection.

Currently, AGVs are programmed to decelerate to half of their nominal velocity when approaching intersections, traversing them at this reduced velocity to significantly reduce the braking distance in case of workers suddenly appearing in the laser scanners' safety areas, and to reaccelerate when leaving the intersection. This procedure significantly reduces the overall efficiency in terms of increased mission time, energy consumption, and mechanical wear on the AGV and is unnecessary in situations where the intersection is free of workers, other vehicles, or obstacles.

The simple solution of the omnidirectional mirror led us to the concept of an infrastructure-based environment perception system that monitors all directions of traffic at a black spot and communicates the results to approaching AGVs. This infrastructure-based cooperative environment perception system allows the PAN-Robots to reduce the efficiency gap. Its objective is to provide the information about the presence or absence of objects near the monitored intersection to each approaching AGV. As detailed in [20], this infrastructure system detects, tracks, and classifies all objects in the vicinity of the monitored area and communicates this information to the control center via wireless communication.

The performance of the infrastructure sensing system was evaluated in a real industrial environment. More than 1,000 measurements were taken of dynamic objects moving in the area monitored by the sensing system. Table 4 summarizes the achieved results, which confirm high measurement precision.

Classification performance was then assessed on the same data set, which included three classes of obstacles: pedestrians, AGVs, and other obstacles. Data were manually annotated to obtain a ground truth. All the obstacles were correctly detected in 100% of the cases, and the system was able to correctly classify the pedestrians in 100% of the cases and AGVs and other obstacles in more than 90% of the cases.

Centralized Data Fusion

A hierarchical data fusion technique is implemented as a cloud system in the industrial environment. Data fusion is necessary because of the presence of different sensing systems that simultaneously acquire data, which need to be made available to the AGV control system for inclusion into the planning and control strategy. Therefore, we introduce a centralized system that is in charge of receiving data from different sources, opportunely merging them, and making them available for the AGV control system. This centralized system defines a global live view of the environment that contains constantly updated information regarding all the entities that populate the industrial environment. As a motivating example, consider the scenario depicted in Figure 4. In this example, an AGV is in the presence of multiple objects as well as pedestrians. Based solely on local sensing [Figure 4(b)], the AGV is able to identify only a limited portion of the objects in its neighborhood. Conversely, when exploiting the global live view cloud service [Figure 4(c)], the AGV is provided with global information that integrates data acquired by different perception systems.

In the proposed architecture, as detailed in [21], information about objects in the scene may be provided by several sources, namely, an onboard sensing system, an infrastructure-based environment perception system, and a 3-D map of the environment. Thus, it is possible to experience issues like data redundancy, inconsistency, ambiguity, noise, and incompleteness. To overcome this problem, the global live view collects all data acquired by the sensors and combines them in a unique and complete representation of the overall system, including the static and dynamic entities that act inside it. In particular, the global live view allows achieving higher-quality information, providing a global updated map representing the static entities (the 3-D map of the plant, the road map), the dynamic entities (the current position and velocity of the AGVs, the position and velocity of currently identified objects), the congestion zones, and the status of the monitored intersections.

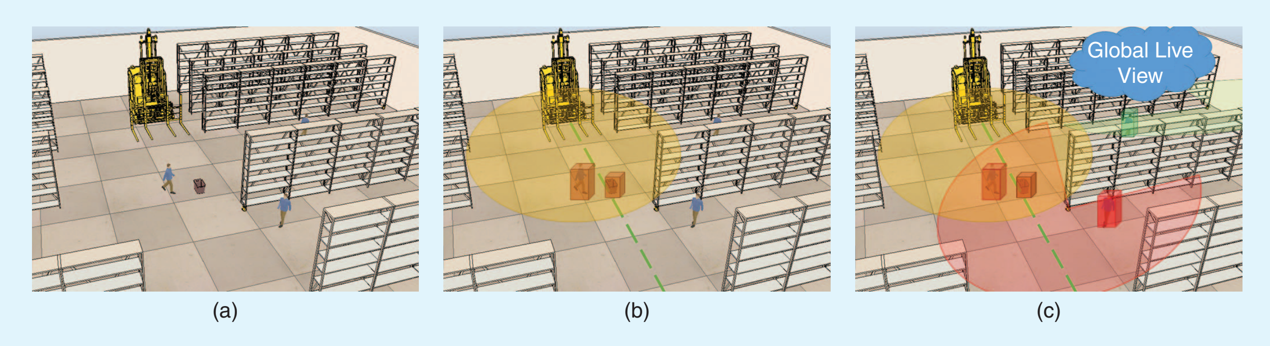

Figure 4. The differences among local and global sensing capabilities. (a) The different objects in the environment, (b) local sensing, and (c) global information from the cloud system.

Fleet and Traffic Management

Because several AGVs share the same environment, the coordination of their motion is a very relevant issue. For this purpose, we propose a novel coordination and path-planning algorithm in the control center that handles the coordination of the fleet. In particular, the motion of the AGVs is coordinated along the road map for optimized mission completion. To optimize mission completion, from a global point of view, it is necessary to develop a methodology for assigning the missions to the AGVs in an optimized manner and, subsequently, to coordinate the motion of the AGVs themselves. Moreover, in case of unforeseen obstacles, it is necessary to replan the path of the AGVs to avoid collisions with the obstacles. Because AGVs are constrained to move along the road map, replanning means finding an alternative path on the road map itself, which is not always feasible. Consider, for instance, the frequent case of unidirectional roads. Thus, if an alternative path cannot be found on the road map, the AGV gets stuck until the obstacle has been removed. To overcome this issue, we propose a method for implementing local deviations from the road map. Fleet and traffic management includes the following modules: 1) global navigation and mission assignment; and 2) local deviation from the road map.

Global Navigation and Mission Assignment

This module is in charge of assigning a mission to each AGV and coordinating the motion of the AGVs along the road map in such a way that the overall fleet performance is optimized. For this purpose, we consider a hierarchical two-layer strategy: the top layer and the bottom layer [22].

Top Layer

The top layer considers the environment from a macroscopic point of view. It is partitioned into sectors, which are bounded regions of space, and we subsequently provide a quantitative traffic measure. This sector partitioning leads to achieving a lumped parameter traffic model that can be used for assigning the mission and defining the overall optimal path to be traveled by each AGV.

For this purpose, we model the set of sectors by means of a directed graph $\mathcal{G}_T$, where each node represents a sector. An edge exists in $\mathcal{G}_T$ between nodes i and j if the ith sector is adjacent to the jth one. That is, a path on the road map exists that is completely contained in $S_i \cup S_j$, starting from S_i and finishing in S_j. A weight can then be assigned to each edge to quantify the traffic in each sector. To this aim, we define $C_i \in \mathbb{R}^+$ as the capacity of the ith sector S_i that is the maximum number of AGVs that can be contained in S_i. This quantity is proportional to the size of the sector itself.

Let $Y_i(k)$ be the number of AGVs traveling along a path contained in S_i at time k. The following traffic measure is then introduced:

$$T_i(k) = \frac{Y_i(k)}{C_i - Y_i(k)}. \quad (1)$$

Namely, a high number of AGVs in a sector (with respect to the sector's capacity) implies high traffic in the sector itself. Edge weights can then be defined by the following time-varying function:

$$\omega_{i,j}(k) = K_{ij} T_j(k) + \delta(b_i, b_j), \quad (2)$$

where $\delta(b_i, b_j)$ is the distance between the centers of S_i and S_j, and $K_{ij} \in \mathbb{R}^+$ is a gain that can be freely tuned. Such a weight aims at providing a measure of the average time necessary for traveling from S_i to S_j. In fact, it is proportional to the distance between the sectors and to the traffic.

These weights can then be utilized for mission assignment. In particular, the proposed methodology consists in exploiting the Hungarian algorithm that represents the optimal algorithm for solving the assignment problem [23]. Generally speaking, the Hungarian algorithm solves the problem of assigning a certain number of activities (i.e., the missions) to a certain number of agents (i.e., the AGVs). In the proposed methodology [24], the cost is determined based on the edge weights defined in (2), which considers both the distance and the current traffic condition.

Subsequently, coordination on the top layer consists in defining, for each AGV, the sequence of sectors to be visited to reach the destination. The D* algorithm [25] is utilized to compute the sequence of sectors, for each AGV, on the weighted graph G_T. Every τ seconds, weights are computed according to (2),

Algorithm 1: Coordination on the Bottom Layer

```
if request [i, q] := true then
    if ∃k ≠ i such that request [k, q] = true then
        Negotiation (Algorithm 2);
    else
        AGV[i] := winner;
    end
    if AGV[i] = winner and status[A_q] = free then
        move;
        request [i, j] := false;
    else
        stop;
        go to line 1;
    end
end
```

Algorithm 2: Negotiation algorithm

```
if pr (AGV[i]) < A_q^p then
    A_q^p := pr(AGV[i]);
end
if pr (AGV[i]) > A_q^p then
    return;
end
if pr (AGV[i]) = A_q^p then
    AGV[i] := winner;
    return;
end
```

and the graph G_T is subsequently updated. The D* algorithm is then utilized for searching the best path on G_T for each AGV.

Bottom Layer

The bottom layer considers the environment from a microscopic point of view. Within each sector, motion of the AGVs needs to be coordinated to guarantee avoidance of deadlocks and collisions. The objective is to assign a path to each AGV in such a way that it can reach the following planned sector (from the top layer coordination).

Because the coordination takes place only within a sector, it can be computed utilizing local information only. This guarantees a significant complexity reduction with respect to considering the entire road map. Hence, within each sector, the path for each AGV is defined along the road map utilizing the standard A* algorithm [26]; this choice is due to the fact that the road map is fixed, and local dynamic changes are not considered.

Figure 5. The local path-planning experiment. (a) The AGV detects an obstacle on its path and sends a request to the global live view. (b) The local deviation path has been computed, and the AGV starts the maneuver to overtake the obstacle. (c) The local deviation path drives the AGV to go around the obstacle. (d) Once the obstacle has been overcome, the AGV returns to the original path.

Conflicts exist in the case of multiple AGVs assigned to simultaneously occupy the same segment. This can happen in the intersection areas, namely, areas where multiple segments intersect. Conflicts are solved considering the intersections as resources to be allocated. Each resource is then allocated only to a single AGV to avoid conflicts. To avoid deadlocks (i.e., two or more vehicles block each other, and none of them can proceed), a negotiation mechanism is utilized.

The overall bottom layer coordination procedure is summarized in Algorithms 1 and 2. In these algorithms, the term pos $(AGV[i])$ represents the position of the ith AGV, and the term request $[i,q]$ represents the request of the ith AGV for the allocation of the qth intersection area. The term pr $(AGV[i])$ is the value of the priority of the ith AGV, and $\mathcal{A}_q^p$ is the value of the priority of the AGV that is winning the current negotiation for the intersection area q.

Local Deviation from the Road Map

In current state-of-the-art AGV systems, no local deviation from the predefined road map is allowed. When an AGV gets stuck on a segment, it has to wait until the obstacle has been removed. This is not efficient and is very time consuming for the whole system. Thus, we developed an algorithm to overcome this issue. Based on the obstacles' positions and on the characteristics of the road map, opportune deviations are computed, utilizing the algorithm detailed in [27], to let the AGV overcome the obstacle. It is worth noting that onboard sensors are not sufficient for safely performing local deviations, because industrial environments include several blind spots. For this reason, onboard sensing is complemented with centralized information from the cloud system. Specifically, when an AGV detects an obstacle on its path (based on onboard sensing), it sends a request to the cloud system, which then provides the AGV with the list of obstacles in its surroundings. The local deviation is then computed only if no dynamic obstacles are present and there is a sufficient amount of free available space.

Experimental validation was carried out in an industrial environment with an AGV controlled to overtake a fixed obstacle on the ground. Snapshots of a representative run of the experiments are shown in Figure 5.

Conclusions

This article presents a system-level overview of the main technological developments achieved by the PAN-Robots European project. In particular, the article mainly focuses on advanced sensing systems and coordination techniques.

The advanced sensing system, composed of onboard and infrastructure sensors, leads to increasing the awareness of the AGVs. While traditional sensing systems, based only on laser scanners, are suitable for guaranteeing safety, those advanced techniques provide the AGVs with classification capabilities, thus making it possible to make high-level decisions in dynamic environments. This represents a mandatory step toward massive deployment of AGVs in environments shared with human operators. Furthermore, traffic-aware mission assignment and motion coordination lead to increasing the overall system performance, even in highly cluttered and dynamic environments, because traffic congestion is heavily reduced.

Even though these results represent a significant improvement with respect to the industrial state of the art, several aspects of AGV systems can still be improved. For instance, coordination among heterogeneous entities has not been considered; other vehicles are treated by AGVs as dynamic obstacles. Including other dynamic entities into the coordination algorithm would lead to the possibility of including, in the same system, AGVs from different manufacturers or AGVs designed to perform different tasks (e.g., different size, different end effector, etc.).

The proposed coordination techniques require the presence of a centralized control unit that acquires position information from the AGVs, computes the traffic model, and defines the motion coordination. AGVs need to constantly communicate with such a centralized control unit; hence, the system is not robust to loss of the communication network. However, it is worth noting that centralized information is needed only for the coordination on the top level. Future work will aim at implementing the coordination on the bottom level in a totally decentralized manner, thus making it necessary to communicate with the central control unit only sporadically when leaving a sector.

Moreover, the proposed sensing techniques require illumination, because they are based on cameras. While illumination is always active in the presence of human operators, there might be applications in which the presence of illumination is not required. These kinds of applications could then largely benefit from alternative sensing technologies (e.g., infrared).

Acknowledgments

This article is written within the PAN-Robots project. The research leading to these results has received funding from the European Union Seventh Framework Program (FP7/2007-2013) under grant agreement 314193.

References

[1] R. Bostelman and E. Messina, "Towards development of an automated guided vehicle intelligence level performance standard," in *Autonomous Industrial Vehicles: From the Laboratory to the Factory Floor*, R. Bostelman and E. Messina, Ed. Philadelphia, PA: ASTM International, 2016, pp. 5–20.

[2] R. Bogue and R. Bogue, "Growth in e-commerce boosts innovation in the warehouse robot market," *Ind. Robot: An Int. J.*, vol. 43, no. 6, pp. 583–587, 2016.

[3] P. R. Wurman, R. D'Andrea, and M. Mountz, "Coordinating hundreds of cooperative, autonomous vehicles in warehouses," *AI Mag.*, vol. 29, no. 1, p. 9, 2008.

[4] H. Andreasson, A. Bouguerra, M. Cirillo, D. N. Dimitrov, D. Driankov, L. Karlsson, A. J. Lilienthal, F. Pecora, J. P. Saarinen, A. Sherikov, and T. Stoyanov, "Autonomous transport vehicles: Where we are and

what is missing," *IEEE Robot. Autom. Mag.*, vol. 22, no. 1, pp. 64–75, Mar. 2015.

[5] L. Sabattini, E. Cardarelli, V. Digani, C. Secchi, C. Fantuzzi, and K. Fuerstenberg, "Advanced sensing and control techniques for multi AGV systems in shared industrial environments," in *Proc. IEEE Int. Conf. Emerging Technologies and Factory Automation (ETFA)*, Luxembourg, 2015, pp. 1–7.

[6] E. Cardarelli, V. Digani, L. Sabattini, C. Secchi, and C. Fantuzzi, "Cooperative cloud robotics architecture for the coordination of multi-AGV systems in industrial warehouses," *Mechatronics*, vol. 45, pp. 1–13, Aug. 2017.

[7] A. Ewald and V. Willhoeft, "Laser scanners for obstacle detection in automotive applications," in *Proc. IEEE Intelligent Vehicles Symp. 2000 (IV 2000),* pp. 682–687.

[8] Y. Zhou, H. Hu, Y. Liu, and Z. Ding, "Collision and deadlock avoidance in multirobot systems: A distributed approach," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 47, no. 7, July 2017, pp. 1712–1726.

[9] F. Oleari, M. Magnani, D. Ronzoni, and L. Sabattini, "Industrial AGVs: Toward a pervasive diffusion in modern factory warehouses," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, Cluj-Napoca, Romania, 2014, pp. 233–238.

[10] S. Silberstein, D. Levi, V. Kogan, and R. Gazit, "Vision-based pedestrian detection for rear-view cameras," in *Proc. 2014 IEEE Intelligent Vehicles Symp.*, pp. 853–860.

[11] R. Benenson, M. Omran, J. Hosang, and B. Schiele, "Ten years of pedestrian detection, what have we learned?" in *Proc. European Conf. Computer Vision*, 2014, pp. 613–627.

[12] M. P. Fanti, A. M. Mangini, G. Pedroncelli, and W. Ukovich, "Decentralized deadlock-free control for AGV systems," in *Proc.* IEEE *American Control Conf. (ACC), 2015*, pp. 2414–2419.

[13] I. Draganjac, D. Miklić, Z. Kovačić, G. Vasiljević, and S. Bogdan, "Decentralized control of multi-AGV systems in autonomous warehousing applications," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 4, pp. 1433–1447, 2016.

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

[15] P. Beinschob, M. Meyer, C. Reinke, V. Digani, C. Secchi, and L. Sabattini, "Semi-automated map creation for fast deployment of AGV fleets in modern logistics," *Robotics Autonomous Syst.*, vol. 87, pp. 281–295, Jan. 2017.

[16] A. Mayra, M. Aikio, K. Ojala, S. Mandici, A. Vatavu, and S. Nedevschi, "Fisheye optics for omnidirectional stereo camera performance evaluation for AGV applications," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, 2015, pp. 225–230.

[17] A. Vatavu, A. D. Costea, and S. Nedevschi, "Modeling and tracking of dynamic obstacles for logistic plants using omnidirectional stereo vision," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, 2015, pp. 3552–3558.

[18] C. Stimming, A. Krengel, M. Boehning, A. Vatavu, S. Mandici, and S. Nedevschi, "Multi-level on-board data fusion for 2D safety enhanced by 3D perception for AGVs," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, 2015, pp. 239–244.

[19] R. Varga and S. Nedevschi, "Vision-based autonomous load handling for automated guided vehicles," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, 2014, pp. 239–244.

[20] M. Boehning, "Improving safety and efficiency of AGVs at warehouse black spots," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, 2014, pp. 245–249.

[21] E. Cardarelli, L. Sabattini, C. Secchi, and C. Fantuzzi, "Cloud robotics paradigm for enhanced navigation of autonomous vehicles in real world industrial applications," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, 2015, pp. 4518–4523.

[22] V. Digani, L. Sabattini, C. Secchi, and C. Fantuzzi, "Ensemble coordination approach in multi-AGV systems applied to industrial warehouses," *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 3, pp. 922–934, July 2015.

[23] H. W. Kuhn, "The Hungarian method for the assignment problem," *Nav. Res. Logist.*, vol. 2, no. 1–2, pp. 83–97, 1955.

[24] L. Sabattini, V. Digani, M. Lucchi, C. Secchi, and C. Fantuzzi, "Mission assignment for multi-vehicle systems in industrial environments," in *IFAC-PapersOnLine,* vol. 48, no. 19, 2015, pp. 268–273.

[25] A. Stentz, "Optimal and efficient path planning for partially-known environments," in *Proc. 1994 IEEE Int. Conf. Robotics and Automation*, 1994, pp. 3310–3317.

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

[27] V. Digani, F. Caramaschi, L. Sabattini, C. Secchi, and C. Fantuzzi, "Obstacle avoidance for industrial AGVs," in *Proc. IEEE Int. Conf. Intelligent Computer Communication and Processing (ICCP)*, Cluj-Napoca, Romania, 2014, pp. 227– 232.

Lorenzo Sabattini, University of Modena and Reggio Emilia, Italy. E-mail: lorenzo.sabattini@unimore.it.

Mika Aikio, VTT Technical Research Centre of Finland, Oulu. E-mail: Mika.Aikio@vtt.fi.

Patric Beinschob, SICK AG, Hamburg, Germany. E-mail: patric.beinschob@sick.de.

Markus Boehning, SICK AG, Hamburg, Germany. E-mail: Markus.Boehning@sick.de.

Elena Cardarelli, University of Modena and Reggio Emilia, Italy. E-mail: elena.cardarelli@unimore.it.

Valerio Digani, Elettric 80 s.p.a., Viano, Italy. E-mail: digani.v@elettric80.it.

Annette Krengel, SICK AG, Hamburg, Germany. E-mail: Annette.Krengel@sick.de.

Massimiliano Magnani, Elettric 80 s.p.a., Viano, Italy. E-mail: Annette.Krengel@sick.de.

Szilard Mandici, Technical University of Cluj-Napoca, Romania. E-mail: mandici.szilard@gmail.com.

Fabio Oleari, Elettric 80 s.p.a., Viano, Italy. E-mail: oleari.f@elettric80.it.

Christoph Reinke, SICK AG, Hamburg, Germany. E-mail: Christoph.Reinke@sick.de.

Davide Ronzoni, Elettric 80 s.p.a., Viano, Italy. E-mail: ronzoni.d@elettric80.it.

Christian Stimming, SICK AG, Hamburg, Germany. E-mail: Christian.Stimming@sick.de.

Robert Varga, Technical University of Cluj-Napoca, Romania. E-mail: robert.varga@cs.utcluj.ro.

Andrei Vatavu, Technical University of Cluj-Napoca, Romania. E-mail: andrei.vatavu@daimler.com.

Sergi Castells Lopez, Coca-Cola Iberian Partners, Madrid, Spain. E-mail: scastells@eu.ccip.com.

Cesare Fantuzzi, University of Modena and Reggio Emilia, Italy. E-mail: cesare.fantuzzi@unimore.it.

Aki Mäyrä, VTT Technical Research Centre of Finland, Oulu, Finland. E-mail: Aki.Mayra@vtt.fi.

Sergiu Nedevschi, Technical University of Cluj-Napoca, Romania. E-mail: Sergiu.Nedevschi@cs.utcluj.ro.

Cristian Secchi, University of Modena and Reggio Emilia, Italy. E-mail: cristian.secchi@unimore.it.

Kay Fuerstenberg, SICK AG, Hamburg, Germany. E-mail: Kay.Fuerstenberg@sick.de.