Multi AGV Systems in Shared Industrial Environments: Advanced Sensing and Control Techniques for Enhanced Safety and Improved Efficiency

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***Abstract*— This paper describes innovative sensing technologies and control techniques, that aim at improving the performance of groups of Automated Guided Vehicles (AGVs) used for logistics operations in industrial environments. We explicitly consider the situation where the environment is shared among AGVs, manually driven vehicles, and human operators. In this situation, safety is a major issue, that needs always to be guaranteed, while still maximizing the efficiency of the system. This paper describes some of the main achievements of the PAN-Robots European project.**

I. Introduction

Goods production flow in manufacturing plants have been largely and deeply automated in the last decades, in order to mainly reduce costs and avoid unsafe work condition. Manufacturing plants often need warehouses for raw materials and final products at the beginning and at the end of the production line. Despite the automation of production, logistics is still marginally automated and till now requires manual operations performed by human workers and hand-operated forklifts. Therefore logistics which is not fully integrated in manufacturing processes arouses inefficiencies together with high risky working conditions for workers [1]. Factory logistics is crucial for the overall production flow and its weaknesses affect the production efficiency and the quality of goods delivery, expecially in terms of product traceability. Bottlenecks and problems in warehouse logistics heavily impact on factory competitiveness on market.

Warehousing in factories of the future can rely on Automated Guided Vehicles (AGVs) and integrated systems for the complete handling of logistic operations (Fig 1). Nowadays these autonomous systems have a market share of about few thousands vehicles sold every year and they are not still ready to be widespread in manufacturing plants. In fact safety, efficiency and plant installation costs are still open problems and technologies are not mature enough to fully support a pervasive diffusion of AGVs. Therefore, innovations to address weaknesses of AGVs and automated warehouse systems will boost capabilities of these logistic solutions bringing them toward a pervasive diffusion in modern factories.

In this paper we analyze technologies developed with the purpose of enhancing the diffusion of AGV systems for factory logistics [2], [3]. AGV systems have been extensively studied in the literature: a comprehensive survey is presented [4], where authors describe the main technologies adopted for localization and guidance of AGVs in industrial environments. The work in [5] describes the use of multiple AGVs for cooperative transportation of huge and heavy loads.

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Fig. 1: Automated warehouse with AGVs

Generally speaking, AGV systems are used for automatizing the movement of goods among different locations in an industrial environment [6], [7]. Typically, an AGV is exploited for picking up a pallet of goods from the end of an automated production line, and bring it to the warehouse, or from the warehouse to the shipment. Each movement operation is generally referred to as a *mission*. The AGV system is handled by a centralized controller, usually referred to as Warehouse Management System (WMS), that is in charge of assigning each mission to be completed to a specific AGV.

When dealing with a single AGV, several strategies can be exploited for single-robot path planning (see e.g. [8]). Conversely, when multiple AGVs share the same environment, coordination strategies need to be adopted in order to optimize the traffic. Typically, the central controller is in charge of coordinating the motion of the AGVs [9]–[13]. In order to simplify the coordination, and to enhance safety of operations, AGVs are often constrained to move along a predefined set of roads, referred to as *roadmap* (Fig. 2).

II. AGVs in Shared Environments

Human workers and autonomous machines usually share the environment in warehouses, so safety is the main issue that must be fully addressed. Safety systems always need to be reliable and robust and commonly rely on certified laser scanners. These sensors are unable to distinguish between different kind of obstacles and do not provide any knowledge

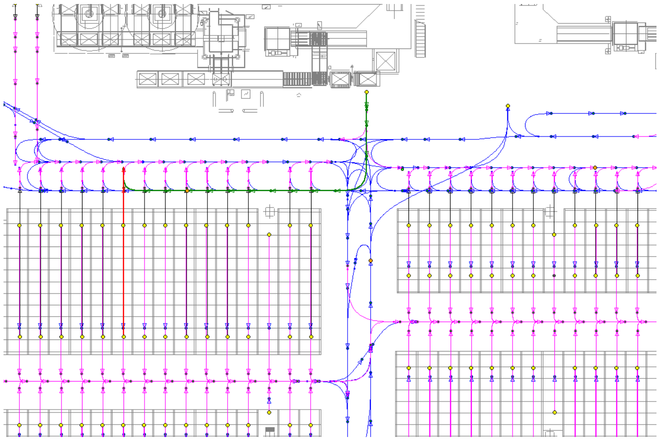


Fig. 2: Portion of the roadmap of a plant

Fig. 3: Human operators sharing the environment with AGVs

about surrounding regions, except from predefined areas. AGVs need then to highly reduce their speed in critical zones in order to guarantee a safe behavior in response to unpredictable situations.

On the same lines, while roadmaps are a very effective manner of reducing the computational resources needed for traffic management, constraining the motion of the AGVs on a finite set of roads severely reduces the flexibility of the system. In particular, this reduced flexibility clearly affects the performance of the system in the presence of unforeseen obstacles. In fact, if an obstacle suddenly appears in front of an AGV, it is necessary to re-plan the AGV's path, in order to avoid collisions with the obstacle. If AGVs are constrained on the roadmap, re-planning means finding an alternative path on the roadmap, which is not always feasible: consider, for instance, the frequent case of mono-directional roads. In this case, if an alternative path can not be found on the roadmap, the AGV gets stuck, until the obstacle has been removed.

Two main reasons can be found that prevent from applying advanced control strategies, that would heavily increase the performance of the system.

First of all, commonly adopted sensing devices are represented by laser scanners, mounted on board each AGV. While these devices are very effective in guaranteeing safety, they are not suitable for obtaining a reliable classification of the acquired object. In particular, it is not possible to distinguish between humans and other kind of obstacles. This is very relevant because humans act in an unpredictable manner: therefore, for safety reasons, it is not possible to assume any knowledge about the intentions of the humans themselves. Hence, if a human is within the sensing range of an AGV, the only safe procedure is to avoid any movement. Conversely, static obstacles could be easily overcome, without having any negative impact on the overall safety of the system. However, the impossibility of reliably distinguishing between humans and other kind of obstacles prevents from the implementation of this kind of advanced control techniques.

The second aspects is related to the fact that sensor systems installed on board each AGV are not able to acquire global information about the surrounding environment. Roughly speaking, they can not *look around corners*. Hence, when approaching an intersection, it is necessary for the AGV to slow down, in order to ensure safety in the presence of unexpected moving objects (or humans).

III. Advanced sensing systems and centralized data fusion

In order to overcome the criticalities highlighted in Section II, an advanced sensing system is proposed to enhance the performance of the AGV system.

The sensing system is composed of two main elements: on board sensors, and infrastructure sensors.

Besides safety laser scanners, it is necessary to equip each AGV with a reliable environment perception system, capable of monitor the entire 360° region around the vehicle. In particular, the on board perception system is composed by multiple laser scanner, positioned around the AGV, together with an omnidirectional stereo vision system consisting of two omnidirectional lenses and two cameras mounted on the top of the AGV. Implementation details can be found in [14].

On board sensors are complemented by additional sensing systems installed on the infrastructure. The idea is similar to the use of hemispherical mirrors mounted above the intersections, that are used by the workers to *look around the corners* (Fig. 4). On these lines, we propose to install laser scanners on specific locations in the environment, in order to provide an efficient monitoring of the black spots. Further details can be found in [15].

Thus, different sensing systems simultaneously acquire data, that need to be made available to the AGV control system, that will include sensing data into the planning

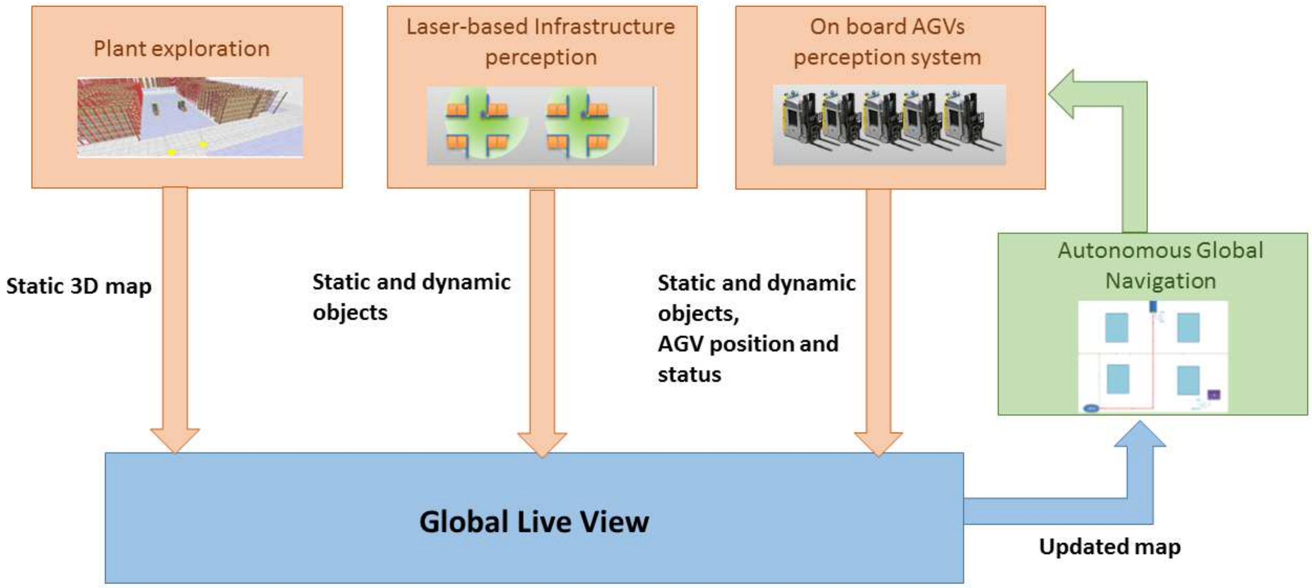


Fig. 5: The general system architecture, designed for obstacle data detection, tracking, classification and fusion.

Fig. 4: Hemispherical mirror mounted above an intersection

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 [16]. The described system architecture is represented in Fig. 5. In particular, the *plant exploration system* provides a static three-dimensional map of the environment, that describe all the static infrastructural elements (e.g. rack, walls, doors, etc.) [17]. Conversely, *infrastructure* and *on board sensors* perceive dynamic objects: in particular, those systems provide object detection, tracking and classification capabilities. Thus, in the proposed architecture, the information about the obstacles in the scene may be provided by several sources, involving the possibility of data redundancy, inconsistency, ambiguity, noise, and incompleteness. To overcome this problem, the Global Live View is introduced, as a module that 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 to achieving higher quality information, providing a global updated map representing the static entities (the 3D map of the plant, the roadmap), 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.

Generally speaking, the information acquired by the infrastructure and on-board perception systems consists of tracked and classified objects, identified with a unique ID. In detail, data regarding each object are:

- Position, orientation, velocity, size.
- Class of the objects: human, manual forklift, AGV, other dynamic object, static object.
- An assessment regarding the quality and reliability of the classification.

The Global Live View is then updated with the information acquired during the operation and *a real-time global map* is generated. This output is shared with the AGV fleet in order to improve their local on-board navigation capabilities and support safe operation.

It is important to guarantee consistency with respect to the real world: each virtual object represented in the map must have a correspondence to a real object of the world. Therefore, the Global Live View performs data fusion to merge data acquired from the different sensors, reducing information redundancy and verifying the presence of data inconsistency and ambiguity.

Data fusion is a very well known problem, that has been extensively studied in the literature. However, it is worth noting that typical solutions consist in the fusion of *low level* data (images, 3D point clouds, laser raw data). This is however not practical for the application we are considering: in fact, for each obstacle candidate, we assume to process medium level features (ID, age, position, orientation, velocity and size) and high level features (class and classification quality) in order to optimize the data transmission time and reduce the network overhead. Therefore, we propose a two level methodology, that implements, separately, medium level and decision level data fusion.

A. Medium level

In the described architecture, dealing data fusion at medium level means processing the object measurements (ID, age, position, orientation, velocity and size) estimated with uncertainty by the on-board and infrastructure systems, as well as the elements inside the static map of the environment.

Thus, from a medium level point of view we introduce a heuristic based on the evaluation of the obstacles occupational area: the principal steps of this solution are represented in Fig. 6. Starting from the bounding boxes delimiting the obstacles detected by the source sensors, the algorithm considers their positions, orientations and occupational overlapping in order to reconstruct a 2D/3D map containing the set of blobs corresponding to the region covered by each candidate. Integrating the information about the velocities and directions estimated for each tracked obstacle, it is possible to discriminate among static and dynamic obstacles. Then, split and merge techniques [18] are utilized to resolve conflicts in the discrimination between blobs that may represent different views of the same object or, alternatively, separated elements. The information representing the fused obstacles is then integrated in a grid map on which free space and unknown regions are modeled, supporting the implementation of path planning and navigation functions (details will be provided in Section IV).

B. High level

The choice of the data fusion strategies for the implementation of the Global Live View can be considered, from an high level point of view, as a classifier combination problem. According to this problem formulation, the static 3D map of the environment, the on-board sensor systems and the infrastructure perception systems represent a set of classifiers that, given an input pattern, provide an output score for each possible class of the system (human, manual forklift, AGV, other dynamic object, static object). This value represents a confidence measure for the class to be the correct class for the input pattern.

Several methods can be found in the literature for solving the problem of classifier combination at measurement level (or type III [19]). Among these methods, we propose to exploit *simple aggregation schemes* at measurement level, like sum-rule, product-rule, average-rule and max rule: despite their simplicity, these elementary combination rules compete with the more sophisticated combination methods, as highlighted in [20]. Moreover, these methodologies are well suited for real time implementation, which is mandatory in this kind of application.

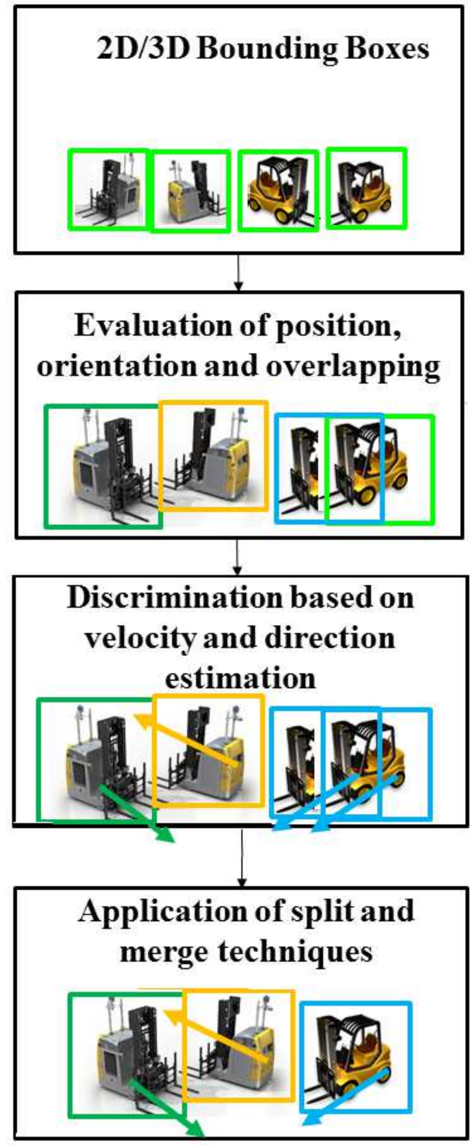


Fig. 6: Principal steps of the heuristic for the Global Live View implementation.

IV. Advanced navigation strategies

The presence of a constantly updated centralized system that collects information about all the objects in the industrial environment, makes it possible to implement advanced techniques for optimizing the navigation performance of the AGVs.

In particular, the problem is that of assigning missions to each AGV, and subsequently planning the path to be traveled for mission completion, in an optimized manner. The proposed mission assignment methodology consists in exploiting the Hungarian Algorithm that, as is well known, represents the optimal algorithm for solving the assignment problem. Generally speaking, the Hungarian Algorithm solves the problem of assigning a certain number of *activities* to a certain number of *agents*. This assignment is based on a matrix of weights, whose element (i, j) corresponds to the cost of assigning the j-th activity to the i-th agent. The optimal assignment obtained after applying the Hungarian Algorithm has the minimum total cost among all possible choices.

In the scenario considered in this paper, *activities* are represented by *missions* to be accomplished, and *agents* are represented by *AGVs*. It is worth remarking that the objective is that of increasing the overall efficiency of the system: therefore, this implies reducing the overall completion time for all the missions.

Therefore, the cost for assigning each AGV to a particular mission should be proportional to the time spent by that AGV to complete that mission. Currently utilized solutions translate this idea defining the cost as a quantity that is proportional to the distance between each AGV and each mission location. In fact, assuming constant speed, travel distance is proportional to completion time. However, this assumption is unrealistic, for multi AGV systems in shared industrial environments. In fact, the presence of unforeseen obstacles, as well as the presence of traffic jams, can significantly slow down AGVs: this leads to the fact that the completion time is no longer proportional to the travel distance.

The coordination of the AGVs along the roadmap can be performed exploiting the strategy presented in [21]. In particular, this coordination strategy consists of a hierarchical control architecture composed by two layers. The higher level performs the coordination over macro-areas of the environment, called *sectors*, while the lower level considers the coordination within each sector. A portion of the roadmap divided into sectors is depicted in Fig. 7.

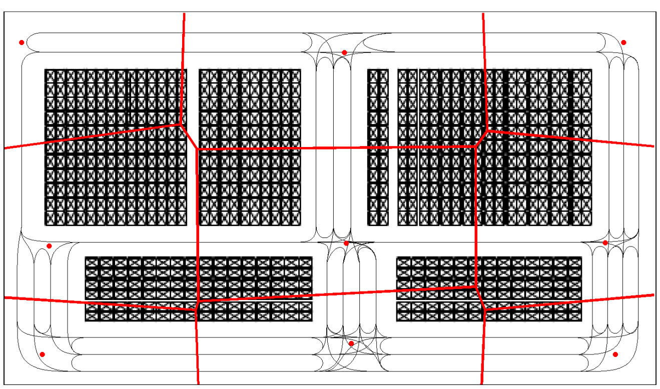


Fig. 7: Portion of a roadmap divided into sectors

Based on the hierarchical division of the roadmap, it is possible to introduce a definition of traffic model that takes into account both the number of vehicles and the presence of obstacles within each sector. Mission assignment and motion coordination is then performed taking into account an opportunely weighted roadmap.

Global knowledge of the obstacles in the environment makes it possible to implement, in a safe manner, obstacle avoidance maneuvers. In particular, exploiting the strategy introduced in [22], it is possible to compute local deviations from the roadmap. These deviations are computed locally by each AGV, relying on information acquired by means of on board sensors, complemented by the a global centralized knowledge of the environment. Local deviations from the roadmap are exploited by the AGVs for avoiding collision with obstacles, while still moving towards their goal. In particular, the proposed algorithm:

- Computes a path that, given the shape of the AGV, guarantees avoidance of collisions with the obstacles, and with any infrastructural element.
- Defines a path that is admissible with respect to the kinematic constraints of the AGVs. In particular, the curvature radius is limited.
- Guarantees that, once the obstacle has been passed, the AGV returns on the roadmap, thus carrying on the original path plan and fulfilling its objective.

A simple but insightful example is represented in Fig. 8. In particular, Fig. 8a represents a ring-like portion of roadmap, where some obstacles (blue rectangles in the picture) are placed to interfere with the motion of the AGVs (an AGV is represented in the picture with a red rectangle).

Based on the obstacles' positions, and on the characteristics of the roadmap, opportune deviations are computed, based on the proposed algorithm. Fig. 8b shows the results obtained in the proposed example: red lines represent the local deviation paths. As expected, feasible paths are computed, since a sufficient amount of free space is always available.

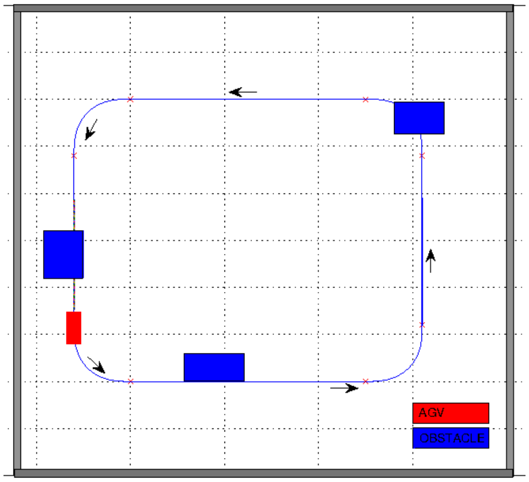
V. Conclusions

Advanced sensing technologies, together with centralized data fusion systems, represent a very effective tool for improving the efficiency of multi AGV systems that share the environment with human operators, where safety is a primary issue. Despite the availability of several technological solutions that exhibit good performance in laboratory environment, a significant effort is necessary to bring those technologies to real working environments. The results obtained within PAN-Robots project represent a significant step towards this direction, bringing together researchers from the academia and from the industries, to develop reliable solutions and validate them in real factory environments.

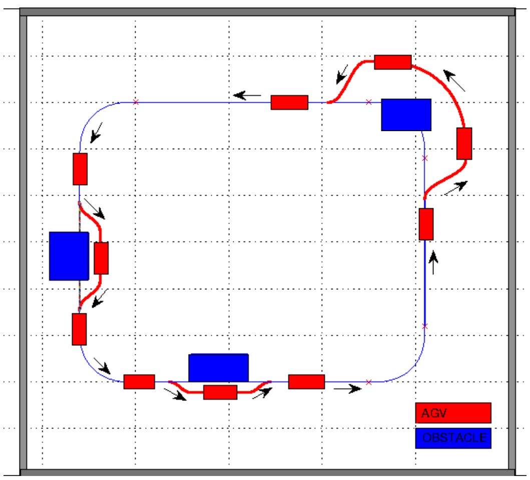
Real world implementation and validation, performed in cooperation with industries, represents a fundamental milestone towards the definition of new safety and technological regulations and standards, that take into account state-of-the-art technologies. The definition of regulations and standards will lead to the possibility of massive deployment of advanced sensing solutions in industrial environments.

Acknowledgment

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



(a) Original roadmap



(b) Roadmap (in blue) with deviations from the original paths (in red)

Fig. 8: Roadmap with several obstacles: red rectangles are the AGV's positions and blue rectangles are the obstacles on the roadmap.

REFERENCES

[1] "Eurostat," http://ec.europa.eu/eurostat.

[2] L. Sabattini, V. Digani, C. Secchi, G. Cotena, D. Ronzoni, M. Foppoli, and F. Oleari, "Technological roadmap to boost the introduction of agvs in industrial applications," in *IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*. IEEE, 2013, pp. 203–208.

[3] F. Oleari, M. Magnani, D. Ronzoni, and L. Sabattini, "Industrial AGVs: Toward a pervasive diffusion in modern factory warehouses," in *Proceedings of the IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*, Cluj-Napoca, Romania, sep. 2014, pp. 233 – 238.

[4] T. Tsumura, "AGV in Japan - recent trends of advanced research, development, and industrial applications," in *Intelligent Robots and Systems' 94.'Advanced Robotic Systems and the Real World', IROS'94. Proceedings of the IEEE/RSJ/GI International Conference on*, vol. 3. IEEE, 1994, pp. 1477–1484.

[5] B. Stouten and A. J. de Graaf, "Cooperative transportation of a large object-development of an industrial application," in *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*, vol. 3. IEEE, 2004, pp. 2450–2455.

[6] B. Mahadevan and T. T. Narendran, "Design of an automated guided vehicle-based material handling system for a flexible manufacturing system," *The International Journal of Production Research*, vol. 28, no. 9, pp. 1611–1622, 1990.

[7] S. Berman and Y. Edan, "Decentralized autonomous agv system for material handling," *International Journal of Production Research*, vol. 40, no. 15, pp. 3995–4006, 2002.

[8] H. Martínez-Barberá and D. Herrero-Pérez, "Autonomous navigation of an automated guided vehicle in industrial environments," *Robotics and Computer-Integrated Manufacturing*, vol. 26, no. 4, pp. 296–311, 2010.

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

[10] R. Olmi, C. Secchi, and C. Fantuzzi, "Coordination of multiple agvs in an industrial application," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, 2008, pp. 1916–1921.

[11] ——, "Coordination of industrial AGVs," *International Journal of Vehicle Autonomous Systems*, vol. 9, no. 1, pp. 5–25, 2011.

[12] D. Herrero-Perez and H. Matinez-Barbera, "Decentralized coordination of autonomous agvs in flexible manufacturing systems," in *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on*. IEEE, 2008, pp. 3674–3679.

[13] D. Herrero-Pérez and H. Martínez-Barberá, "Decentralized traffic control for non-holonomic flexible automated guided vehicles in industrial environments," *Advanced Robotics*, vol. 25, no. 6-7, pp. 739–763, 2011.

[14] M. Drulea, I. Szakats, A. Vatavu, and S. Nedevschi, "Omnidirectional stereo vision using fisheye lenses," in *Intelligent Computer Communication and Processing (ICCP), 2014 IEEE International Conference on*, Sept 2014, pp. 251–258.

[15] M. Boehning, "Improving safety and efficiency of agvs at warehouse black spots," in *Intelligent Computer Communication and Processing (ICCP), 2014 IEEE International Conference on*, Sept 2014, pp. 245–249.

[16] E. Cardarelli, L. Sabattini, C. Secchi, and C. Fantuzzi, "Multisensor data fusion for obstacle detection in automated factory logistics," in *IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*. IEEE, 2014.

[17] P. Beinschob and C. Reinke, "Advances in 3d data acquisition, mapping and localization in modern large-scale warehouses," in *Intelligent Computer Communication and Processing (ICCP), 2014 IEEE International Conference on*, Sept 2014, pp. 265–271.

[18] B. Parvin and G. Medioni, "Segmentation of range images into planar surfaces by split and merge," in *Proc. of International Conference on Computer Vision and Pattern Recognition (CVPR86)*, 1986, pp. 415–417.

[19] L. Xu, A. Krzyzak, and C. Suen, "Methods of combining multiple classifiers and their applications to handwriting recognition," *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 22, no. 3, pp. 418–435, May 1992.

[20] L. I. Kuncheva, J. C. Bezdek, and R. P. Duin, "Decision templates for multiple classifier fusion: an experimental comparison," *Pattern recognition*, vol. 34, no. 2, pp. 299–314, 2001.

[21] V. Digani, L. Sabattini, C. Secchi, and C. Fantuzzi, "Hierarchical traffic control for partially decentralized coordination of multi agv systems in industrial environments," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2014.

[22] V. Digani, F. Caramaschi, L. Sabattini, C. Secchi, and C. Fantuzzi, "Obstacle avoidance for industrial AGVs," in *Proceedings of the IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*, Cluj-Napoca, Romania, sep. 2014, pp. 227 – 232.