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Multi-Layered Costmap-based Navigation of Heterogenous Mobile Robots for Material Handling Application

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Résumé – Dans le système actuel de manutention de matériel (MHS), la planification de trajectoire des robots mobiles autonomes (AMRs) repose uniquement sur la géométrie de l'espace de configuration, ce qui réduit les performances opérationnelles en milieu dynamique. Ainsi, plusieurs facteurs peuvent affecter l'efficacité de la navigation, notamment les sujets dynamiques opérants dans l'environnement partagé tels que les risques de collision et les conflits de navigation, ou les sémantiques statiques, tels que la friction et les pentes du sol. La prise en compte de ces aspects qui décrivent l'activité dans l'environnement opérationnel permet d'adapter la trajectoire à prendre ainsi que le mouvement de manière efficace. Cet article propose une architecture décentralisée pour identifier et partager les données liées à l'environnement entre les différentes plateformes. Les risques de collision non sécurisés auxquels est confronté chaque AMR sont modélisés à l'aide de la distribution par noyau et envoyés au serveur SGV-System sous forme de couche sémantique à fusionner en conséquence. Ensuite, la cartographie globale multi-couches résultante est publiée sur toutes les plateformes mobiles à des fins de planification de trajectoire. Une simulation est réalisée pour évaluer la méthode proposée en la comparant aux techniques de planification les plus récentes. Les résultats montrent l'efficacité de la méthode de navigation proposée.

Mots clés – **Navigation autonome, efficacité énergétique, Véhicule Autoguidé, planification de la trajectoire.**

Abstract – In the current Material Handling System (MHS), Autonomous Mobile Robots (AMRs) path planning relies solely on the geometry of the configuration space, resulting in lower operating performances in a dynamic environment. Thus, several factors may affect the efficiency of navigation, this includes the dynamic subjects operating within the shared environment such as collision risks and navigation conflicts, or static semantics such as floor friction and floor slopes. Considering these aspects that describe the dynamic activity within the operating environment allows to adapt the motion accordingly. This paper proposes a decentralized architecture to share the different static and dynamic semantic information related to navigation conflicts. Unsafe collision risks confronted by each AMR are modeled using kernel distributions and sent to the SGV-System Server as a semantic layer to be merged accordingly. Then, the resulting multi-layered global costmap is published to the mobile platforms in order to be used for path planning purposes The simulation is conducted to evaluate the proposed method while comparing with the state-of-the-art planning techniques. The results show the effectiveness of the proposed navigation method.

Keywords – **Autonomous navigation, energy efficiency, Autonomous Mobile Robot, trajectory planning.**

1 INTRODUCTION

Manufacturing is and has always been a significant part of the global economy. The World Bank Group reported in 2021 that the manufacturing sector constitutes 17% of the world's gross domestic product (GDP) (World Bank national accounts data). With the advent of automated machinery, high-scale manufacturing has been possible. Nevertheless, the rigid classical computer-aided systems are lagging, unable to meet modern demands. This is primarily due to the growing and varying requirements on production and manufacturing services over recent decades. Furthermore, mega-warehouses have taken shape lately as e-commerce has boomed (Boysen et al., 2019). Whether for storing raw materials for the production unit, or finished products intended for retailing, warehouse logistics have reached an unprecedented complexity and size. Therefore, carrying loads between different storage areas hundreds of meters need to be traveled safely and efficiently.

Automated freight solutions had been already introduced in industries and warehouses to improve intralogistics since the mid-twentieth century. Automated Guided Vehicles (AGVs) are used to automatize material handling tasks. However, these systems are inflexible and may lead to potential fleet deadlocks (Makris, 2021; Qi et al., 2018). As technologies regarding theonomous mobile navigation are at their culmination point, extensive works have emerged for material handling purposes (De Ryck et al., 2020). Autonomous Mobile Robots (AMRs) or also known as Self-Guided Vehicles (SGVs) are autonomous laser-guided mobile platforms that effectively enable their deployment on a larger scale compared to the previous generation platforms. Their ability to navigate autonomously in free spaces is a key enabler to

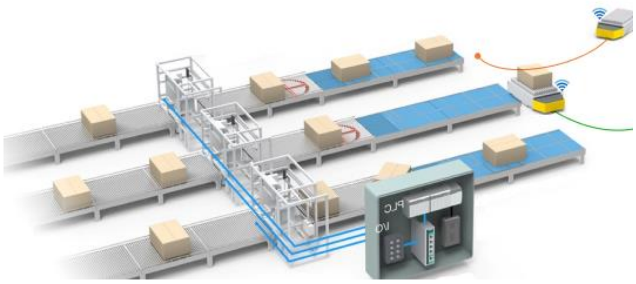

Figure 1. Material Handling System for Reconfigurable Manufacturing System.

increase the number of completed tasks despite workload complexity (Graba et al., 2020).

As Reconfigurable Manufacturing Systems (RMS) requires highly efficient and flexible indoor transportation of goods, AMRs require traveling long distance, carrying large loads, and dynamically interacting with their environments. Nevertheless, AMRs are battery power systems whose energy autonomy is yet a factor that limits the self-sufficiency of the MHS. Although these mobile platforms are required to process continuously for several hours, the battery source remains one of the main constraints for service durability (Graba et al., 2020).

The backbone of autonomous motion is path planning, and it is divided into two main parts, global and local planning. Global planner produces a geometric path from the actual node to the destination node considering the static obstacles known a priori, and the local path execution takes as input the global path and progressively generates motion that considers possible dynamic obstacles. However, the limits of such an approach were particularly highlighted in multi-vehicular scenarios. In a decentralized SGV-System, each vehicle independently generates global trajectories. As the AMRs fleet operates in shared dynamic indoor space, it is most likely that a vehicle encounters conflict while traveling to its destination, as shown in Figure 1. Consequently, to ensure that the AMR reaches its destination efficiently while avoiding collision, both planners have complementary roles. However, modern MHSs have become increasingly complex and large, as a result, the ability to plan efficient paths is crucial for safely and efficiently traveling long distances in a dynamic environment while transporting loads (Mohammadpour et al., 2022). In addition, AMRs must contend with continuous environment changes. Therefore, from an autonomous navigation standpoint, these dynamic changes can result in a conflict, wherein the AMR's operation is hindered by new static and dynamic obstacles (Lopez et al., 2017).

The remainder of this paper is organized as follows. Section 2 states the problem and gives the literature review. Section 3 presents the methodology to reach the objective. Section 4 provides the simulation to test the proposed algorithm. Finally, conclusions are drawn in Section 5.

2 Problem Statement & Literature Review

So far, state-of-the-art of autonomous mobile navigation has focused on smooth criteria of motion. Recent works have shown the limited performances of the actual global path design and local path execution, where, the inefficiency has been particularly highlighted in multi-robot scenarios (De Ryck et al., 2020; Fragapane et al., 2021; Graba et al., 2020; Patle et al., 2019). As a heterogenous AMR fleet operates in shared indoor space, it is most likely that these platforms avoid each other with motions generated by the local planner. However, highly dynamic motions due to acceleration and rotation are very demanding in terms of power and battery effort (contributing to fast battery degradation),

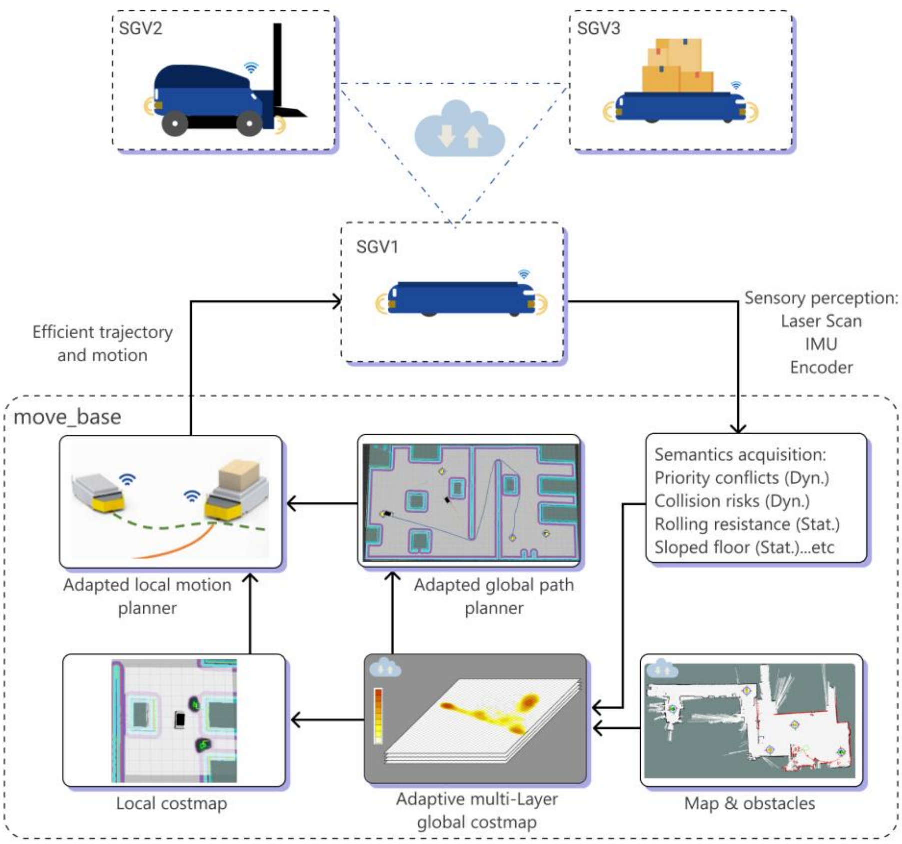

Figure 2. Multi-Layer framework with static and dynamic semantics definition.

mainly in the case where heavy loads are transported (Meißner & Massalski, 2020). Therefore, as an assumption in this paper, limiting these efforts would improve the navigation efficiency and the long-term energy consumption of the overall fleet system.

When an unexpected change occurs in the configuration space or an unforeseen obstacle arises, the AMR must suddenly decelerate or brake to a complete stop in a particular area to avoid a collision. This is known as a conflict, as illustrated in Figure 3. Conflict avoidance approaches require local coordination between AMRs when a conflict is imminent. Dynamic online obstacle avoidance is the simplest example of this technique (Chakravarthy & Ghose, 1998; Dong et al., 2021). Time Elastic Band (TEB) is a robust local path planner with obstacle avoidance capabilities (Rösmann et al., 2017). However, when two or more AMRs are conflicting, TEB might be less effective as the conflict may just be shifted to an adjacent space when both try to avoid each other. Capelli et al. (2019) propose a method that interprets approaching obstacle intentions through motion legibility. In Rathi & Vadali (2021), intentional exchange via explicit communication is proposed to determine "who goes first". Recent learning-based approaches (Wang et al., 2021; Xiao et al., 2020; Xu et al., 2020) have been studied to address the real-time tuning of planner parameters such as speed and acceleration. However, end-to-end learning approaches are data-intensive, requiring hours of training data from expert demonstrations or trial-and-error tests. Furthermore, learning-based methods often lack safety and explainability, which are essential features for AMR operating in environments such as warehouses with countless potential scenarios.

Motions failures and systemic replanning are the bottlenecks in an SGV-system, implying a cost-ineffective navigation, especially when the environment is dynamic and cluttered. Different conflict detection and resolution attempts have been proposed in the literature. The proactive approaches described previously have shown their capacity to deconflict complex scenarios. However, to the extent of our knowledge, the energy efficiency of these strategies, and their effect on battery degradation is overlooked in the literature.

3 PROPOSED METHOD

Although a fleet of AMRs enables system scalability and flexibility, on the other hand, they may suffer from a lack of data from the operating environment. As SGV-System Server may involve several heterogeneous types of AMRs, the path planning strategies required for each platform are challenging due to the versatility of the manufacturing environment.

To provide adaptive navigation to the fleet, a platform-independent framework is proposed in this paper, in order to incorporate different semantics data as a costmap layer that will

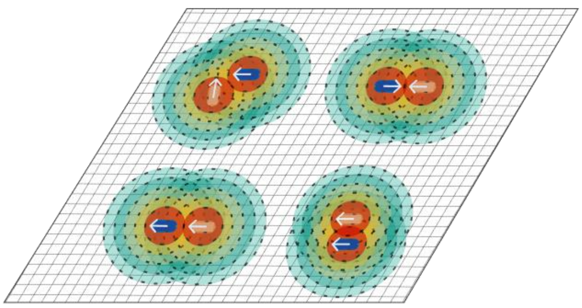

Figure 3. Collision risks scenarios of two Self-Guided Vehicles.

adapt the planning performance. We can classify the semantic information of the manufacturing environment into two categories, non-probabilistic and probabilistic. The non-probabilistic semantic is information that is static and characterizes an aspect of the environment such as the sloped floor, rolling resistance…etc. On the other hand, probabilistic semantics is event-related information from the dynamics of the environment that affects the navigation performances of one or several AMRs for instance the reconfigurability of the manufacturing space, or collision risks. Once the semantic data are processed by the SGV-system server, the data represented in the costmap layer are implemented in ROS (Robot Operating System) in which these static and dynamic semantics are modeled. The data type considered in this paper is collision risks. Figure 2 shows the proposed framework that considers semantic data.

3.1 SGV-System Server:

In the proposed decentralized paradigm, the SGV-system server is data-centric, as illustrated in Figure 4. In other words, any operating AMR can be a data publisher and data subscriber to the SGV-system server (Jeong et al., 2022). When an AMR characterizes a type of semantic, in our case collision risks, the

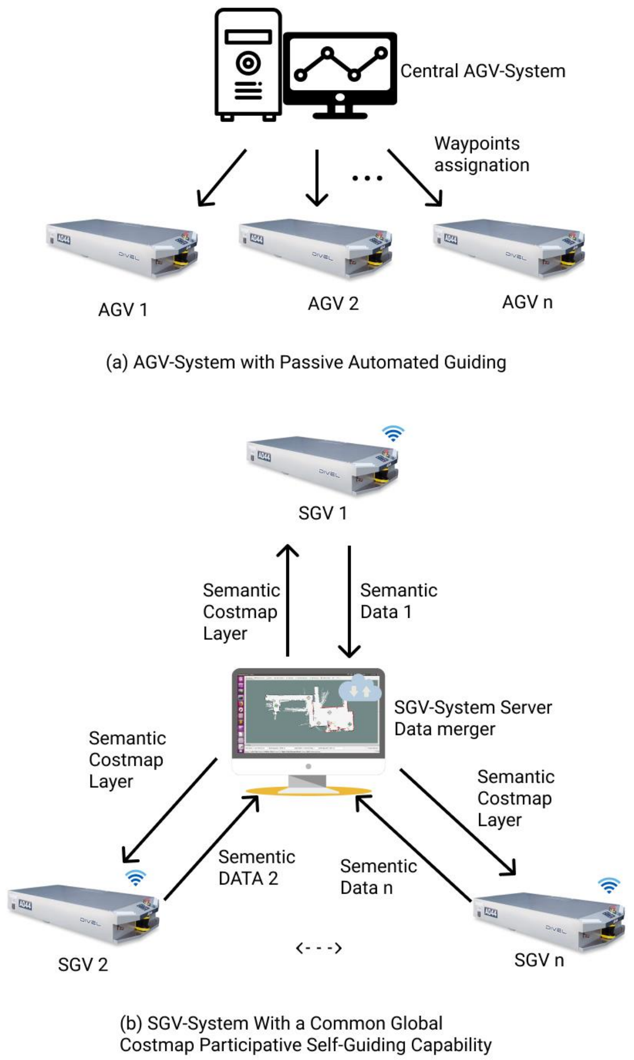

Figure 4. (a) Classical AGV-System architecture (b) Proposed SGV-System architecture

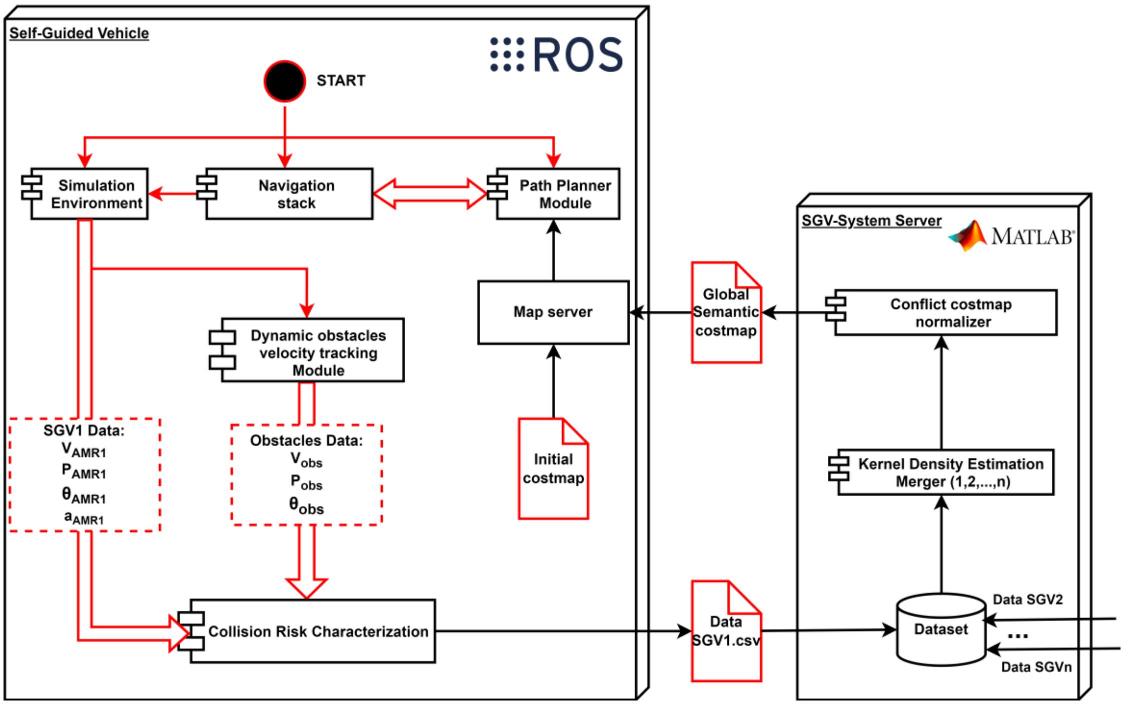

Figure 5. Dataflow of between the SGV and the SGV-System Server

resulting data is sent to the SGV-system server. After collecting different semantics, the server processes them by merging different data in accordance with the type and location. Then, a global multilayer costmap is generated and dispatched to all mobile platforms. This makes the burden of explicit communication between the AMRs much more efficient, as different data types can be exchanged between the latter.

3.2 *Data merger:*

To process data from different mobile platforms, we used the kernel merging method proposed by (Zhou et al., 2003). The kernel estimation module aims at providing the quantification of the severity of the collision-risk over the configuration space. This is modeled by collecting the *collision_risk* trigger provided by the local planner of the AMR in different locations the kernel function K is a nonparametric technique generates normal distribution based on observation for every AMRs, as shown in Figure 6. The normal kernel is chosen based on a decreasing speed profile when braking safely and smoothly. As the

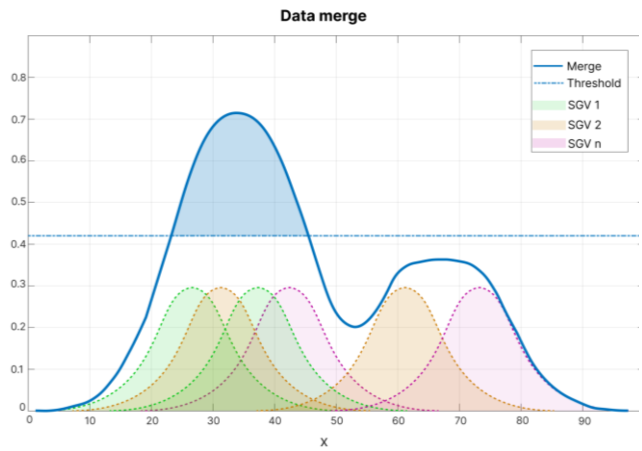

Figure 6. Data merge of kernel densities of collision risks collected from different SGVs.

estimation involves spatial data, the formulation of the data merger is defined using the following equation:

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} \frac{w_i}{h} K\left(\frac{x-S_i}{h}\right) \ \ where \ \sum_{i=1}^{n} w_i = 1$$

$$K\left(\frac{x-S_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-S_i}{h}\right)^2}$$

$$h \approx 1.06\hat{\sigma}n^{-\frac{1}{5}}$$

where $\hat{f}(x)$ is merged density estimation that corresponds to n sample points; K is a kernel function with bandwidth h ; s_i is the i^{th} dataset sample from different AMRs; w_i is the corresponding weight observed collision risk, and $\hat{\sigma}$ is the standard deviation n sample points.

3.3 *Global Costmap:*

The costmap is a representation of the configuration space that consists of discrete cells with a grayscale value, used to calculate minimum motion cost in global and local path planning algorithms. Lu et al. (2014) proposed the layered costmap to organize the configuration space into a list of ordered layers that describe specific functionalities of the environment. The primary layer is the static map, which is built using the Simultaneous Localization And Mapping (SLAM) algorithm (Bailey & Durrant-Whyte, 2006) and represents the static obstacles and walls. Additional layers are introduced as ROS plugins, such as the inflation layer that adds a buffer distance from obstacles. These plugins are combined with the static map layer to create a multi-layered global costmap. The paper aims to avoid collision risk for Autonomous Mobile Robots (AMRs) and incorporates a merged semantic layer into the global costmap, which is shared amongst AMRs to enable each mobile platform to generate collision-free paths.

4 SIMULATION

4.1 Simulation Setup:

In this section, we detail the simulation process used to assess the proposed approach in the open-source ROS-Gazebo simulation environment (see Figure 5). The simulation includes two model-based Autonomous Mobile Robots (AMRs), SGV1 and SGV2, deployed in a 3D indoor warehouse-like environment. The environment also includes four dynamic objects, two pedestrians, and two forklifts, moving within the configuration space, as shown in Figure 7. Conflict scenarios are created by the inclusion of narrow areas such as corridors and blind zones like corners, as illustrated in Figure 3. Laser scanners are used in both the simulation and experimental tests and the map is constructed using the SLAM algorithm (Bailey & Durrant-Whyte, 2006) before the navigation tests.

The navigation algorithms are implemented using ROS and the navigation stack framework. The two-stage navigation approach is used, with the A* global planner (Tang et al., 2021) searching for the geometrical path to the next station while considering the known static obstacles. The Time Elastic Band (TEB) is then used as the local planner to generate optimal motion to follow the planned global trajectory (Rösmann et al., 2015).

A pair of Sick MicroScan laser scanners models are used, placed in a 360° configuration with a range of up to 40 meters. However, for this paper's scope, and to minimize sensor data volume and uncertainties, the look-ahead perception distance is limited to 5 meters from the SGV.

The TEB is configured to keep the AMRs away from obstacles while moving along the global path. The linear speed and angular speed of the autonomous platforms are set to 1.0 m/s and 0.8 rad/s, respectively, while the maximum linear and angular accelerations are set to 0.5 m/s^2 and 0.6 rad/s^2, respectively.

Both SGV1 and SGV2 share the configuration space simultaneously, and a 0.5 m inflation layer is set from all known static obstacles for safety purposes. SGV1 is assigned to go from station S1→S2→S3→S4→S1 repeatedly, while SGV2 is assigned to S4→S1→S2→S3→S4 repeatedly as well. We define a completed cycle when all stations are visited. In all simulations, the platforms transport a constant 50 Kg package to simulate a real-world scenario.

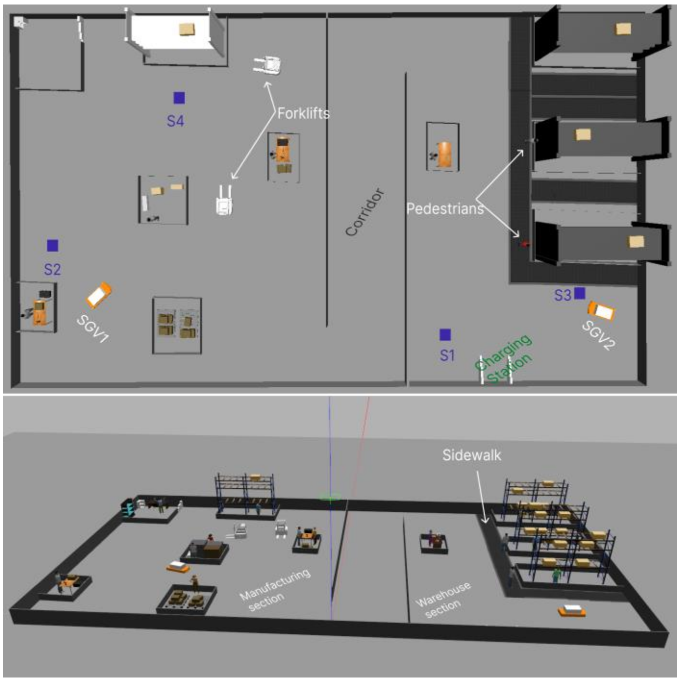

Figure 7. 3D simulated environment in Gazebo.

The SGVs must avoid the randomly deployed dynamic obstacles in the environment, including the forklifts and the pedestrians, while also confronting each other. The pedestrians are walking in a dedicated zone not specified in the costmap to create a realistic scenario, while the forklifts operate randomly. The forklifts' and pedestrians' velocities are set to 0.8 and 0.5 m/s, respectively.

The simulation is conducted for 6 hours, and the collision risks are recorded using the Time-to-Collision index (Bosnak & Skrjanc, 2017). The performance metrics used to support the contribution are the average consumed energy per cycle, the average path execution time per cycle, and the percentage of critical failures. We define failure as when the vehicle is stuck in a particular position or takes more than the required time to arrive at the next station.

4.2 Simulation results:

During the six-hour simulation in an MHS warehouse, the SGVs were assigned to follow a specific path. Figure 8 illustrates the expected trajectory before and after incorporating the semantic layer that considers potential collision risks. It was noted that the estimate of collision risks remained stable after the fourth hour, as most of the critical collision risks were defined in the configuration space. Table 1 compares the navigation performances of SGV1 and SGV2 before and after the addition of the semantic layer. The proposed implementation reduced the average execution time per cycle by 10% for SGV1 and 8.1% for SGV2. Furthermore, the capacity of the SGVs to move between stations quickly improved after adding the semantic layer to the master costmap. In addition, both SGVs showed better performance in reaching their destinations with low critical brakes, resulting in a reduction of previously persistent collision risks by 40-43%. This reduced critical collision risk makes it safer and less likely to experience severe collisions while navigating dynamic obstacles such as unforeseen pedestrians. Finally, Table 1 also shows that the average energy consumed was reduced by up to 13% for both vehicles over the entire duration of the simulation.

Tableau 1. Interstation navigation performance of the two vehicles

Paths	S1→S2→S3→S4→S1				Efficiency (%)
Cost Map	Original Global Costmap		Global Costmap + Semantic Layer		
Tests	SGV1-1	SGV2-1	SGV1-2	SGV2-2	
Average time (s)	162.1	166.9	147.0	153.3	9.3 %
Critical Failure (%)	23.2	24.6	14.5	13.9	43%
Energy Consump. (KJ)	31.7	32.1	27.8	28.9	12.3 %

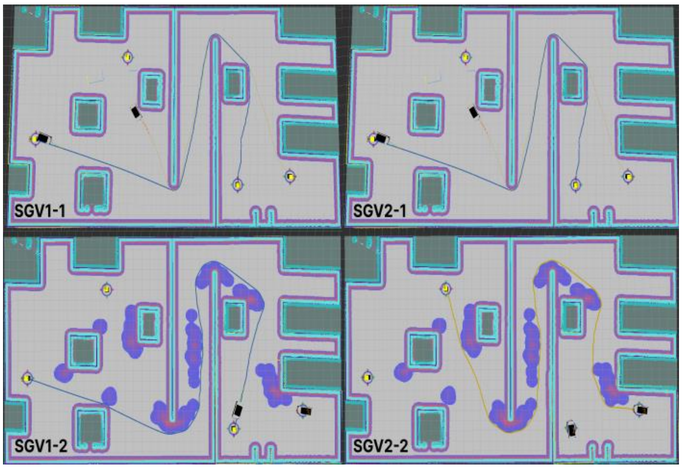

Figure 8. The global planned trajectory of the SGVs prior and after adding the semantic layer.

5 Conclusion & Perspective

As several AMR may navigate in cluttered spaces, dynamic obstacles can unsafely deteriorate the operation performances. Global trajectory design has a major role in increasing the performance of navigation in a dynamic environment. In this study, we proposed a new methodology to model the different collision risks encountered by the AMR fleet over the configuration space. The model is then represented as a global costmap to be considered at the global trajectory design level. This method is tested in a simulated environment with different types of dynamic obstacles. The results have demonstrated a significant increase in the smoothness of the executed trajectory, which limits the maximum power required by the AMR to reach its destination. Thus, the hypothesis is confirmed as the total energy consumption is lower than when using geometric planning by up to 12%, although the AMR travels a longer distance when avoiding conflict areas. Another aspect of the application is the execution time, as solving conflicts are often time-consuming avoiding collision risk area that fastens the task execution. In perspective, it is important to test the algorithm in a larger space "megawarehouses" in which a larger number of heterogenous AMRs are operating with other dynamic subjects.

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