Concept for Safe Interaction of Driverless Industrial Trucks and Humans in Shared Areas

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Abstract. Humans still need to access the same area as automated systems, like in warehouses, if full automation is not feasible or economical. In such shared areas, critical interactions are inevitable. The automation of vehicles is usually tied to an argument on improved safety. However, current standards still rely also on the awareness of humans to avoid collisions. Along with this, modern intelligent warehouses are equipped with additional sensors that can help to automate safety. Blind corners, where the view is obscured, are particularly critical and, moreover, their location can change when goods are moved. Therefor, we generalize a concept for safe interactions at known blind corners to movements in the entire warehouse. We propose an architecture that uses infrastructure sensors to prevent human-robot collisions with respect to automated forklifts as instances of driverless industrial trucks. This includes a safety critical function using wireless communication, which sporadically might be unavailable or disturbed. Therefore, the proposed architecture is able to mitigate these faults and gracefully degrades the system's performance if required. Within our extensive evaluation, we simulate varying warehouse settings to verify our approach and to estimate the impact on an automated forklift's performance.

Keywords: Driverless industrial trucks · Human-robot interaction · Infrastructure sensors · Warehouse

1 Introduction

Humans and automated systems work together in shared areas of a warehouse. Thanks to advances in artificial intelligence, robots can already perform many tasks, but some are not yet feasible or economical. Therefore, co-working of humans and machines is an important factor for future competitiveness [28].

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Efficiency of a warehouse can be greatly improved when the flexibility of human workers and carrying power of automated guided vehicles (AGVs) are available in the same area [30]. Especially autonomous mobile robots (AMRs), which can be considered a subgroup of AGVs with a high degree of autonomous control [7], are used for this purpose. Segregation of automated machines and human workers, e.g., placing robots in dedicated safety cages, cannot be used to ensure safety in shared areas and new safeguards are needed.

This paper explores the safe movement of driverless industrial trucks in the presence of human workers. Within in-house transportation, industrial trucks are a major source of accidents [11] that can harm driver or bystanders. Driverless industrial trucks, such as AGVs, already remove the need for a driver. Further, the safety requirements for driverless industrial trucks [17] provide guidelines to reduce the inherent risk of human-machine-collisions. For some tasks, completely restricting the operation of AGVs and human workers to separate areas can remove the advantages of automation. This necessitates shared areas in which both operate. AGVs are equipped with safe perception capabilities, e.g., lidars or radars, and have to slow down or come to a complete stop, when obstacles in the surrounding are detected [31]. However, a major challenge in warehouses is the limited line of sight, e.g., due to walls, shelves, or storage. In this case, corners become a potential point of risk [13]. Moreover, their location may change when goods are moved. Without an external source of information, constraints need to limit the operation of AGVs in these areas, i.e., no operation or strongly reduced speed [4], as AGVs themselves cannot detect occluded human workers. Human workers also cannot look around the corners and thus, are also in risk of provoking collisions [26]. One solution to mitigate such risks are safety rules for personnel. For example, priority could be given to driving AGVs by persons stopping at each corner and ensuring that there are no AGVs and aided by visual or sound warning signals. However, those measures are likely to be ignored, bypassed or overlooked during work, especially if they are perceived to be rarely useful and reduce efficiency [16]. In this paper, we study how utilizing sensors in the infrastructure can contribute to safer operation of automated forklifts – a specific type of AGV – in the areas where human workers are allowed to enter. As main contributions, we analyze the problem of safe automated movement in a warehouse. Moreover, we present an architecture and novel concept exploiting infrastructure sensors for achieving safe and efficient movements of automated forklifts in shared areas of a warehouse. Our approach is evaluated by thorough simulations of warehouse scenarios and analyzing the adherence to safety goals and operation performance. With the results of this paper, we aim for showing how safety can be achieved, even in the presence of potentially critical blind spots, by dynamically adjusting the forklift's performance with respect to the available perception information.

The remainder of this paper is structured as follows. Section 2 introduces relevant safety standards, related work, and conflict detection at know blind corners. Section 3 describes the used architecture and generalizes conflict detection to the entire warehouse. Section 4 explains the warehouse scenarios, the metrics and the results of our extensive evaluation, before we conclude the paper in Sect. 5.

2 Critical Interactions in Warehouses

Within intra-logistics, industrial trucks are involved in many accidents [11]. Even with extensive guidelines [3, 34] and trainings [9] available for forklifts, a more than proportional number of incidents involving them are serious or fatal. Forklift automation already takes the driver out of harm's way. However, full automation of warehouses is not always feasible or economical and humans may still need to access the same area as forklifts. Therefore, automation must be designed carefully to not increase the risk for these humans.

2.1 Safety Standards for Driverless Industrial Trucks

Several safety standards for mobile machinery are being established. Within the European Union, laws such as the Machine Directive and national laws for protection of human safety are complemented by ISO and IEC standards that describe general design principles, cover aspects for a wide range of machinery, or deal with particular machines [24].

For example, ISO 3691-4 [17] defines the requirements for driverless industrial trucks including unmanned forklifts, AGVs and associated systems. It considers four main kinds of access zones. The enclosed space of a **confined zone** does not need personnel detection. However, only authorized personnel may access the zone after all movement was stopped. A **restricted zone**, like a very narrow aisle, may be entered only by authorized persons. In an **operating hazard zone**, a person can be exposed to a hazard. Therefore, audible or visual warnings and a low speed of $0.3\,\frac{\mathrm{m}}{\mathrm{s}}$ are required. Higher speeds like $1.2\,\frac{\mathrm{m}}{\mathrm{s}}$ are only allowed under specific conditions. Only the **operating zone** allows operation at rated speeds and has a minimum clearance (i.e. 0.5 m wide) on both sides of the path and in the direction of travel.

For autonomous machinery, two main problems are currently seen in the standardization of safety requirements [36]: A gap between requirements of these standards and state-of-the-art complicates more gradual paths to develop systems and the safety standards are mainly for machine manufacturers, while the work process and worksite should provide guidance to their implementation.

This research aims for understanding how to ensure safe and efficient operation of AGVs in areas shared with human workers. For AGVs to use up to their rated speed, we target the whole warehouse to be an *operating zone*. Therefore, the initial two requirements for the system were: Gaps between the machine and walls must be at least 0.5 m and active personnel detection mechanisms.

According to the standard, detection of persons is required in the direction of travel only. This is tested using static cylinders [17, 18]. However, this ignores possible persons nearby the machine, even when a collision could be caused by the person stepping into the machine's path. Only the requirement of sufficient space around the AGV and the person's awareness of the machine assure safe interactions between AGV and human worker. Thereby, in such systems, human beings still take the responsibility for avoiding collisions. In future however, safety of a technical system is also envisioned to encompass freedom from danger [1]. Therefore, the responsibility of avoiding a collision needs to be moved from humans to the automated forklift.

2.2 Cooperation and Coordination

Safe behavior has been taught to human drivers of forklifts for a long time, e.g., slowing down, sounding the horn, and looking around [9]. While a simple flashing light – even when mounted in a highly visible location – might not always prevent (near) collisions with a robot [15], light spots or symbols projected into the direction of travel or around the forklift can improve awareness similar to beeper alarms for reversing [6].

Different algorithms claiming to provide proven safe motion of autonomous mobile robots have already been explored [2,20]. However, these methods are limited by the information available to the robot. Exchanging messages with robots in the neighborhood helps decentralized coordination [12] and infrastructure-based sensors can provide information on other actors in the warehouse. Real-time locating system (RTLS) based on camera-data [19] or ultra wide band (UWB) technology [30,35] can locate persons with a precision of at least 15 cm in a warehouse and predict the paths of workers [21]. However, the safety integrity of such locating and prediction systems needs to be assessed. For reliable detection, more expensive and less feature rich safety sensors are often used. Spaghetti charts can be created from the recorded movements to further analyze and improve safety [5].

The AGV must receive updates on this changing information continually. Several methods to centrally coordinate vehicles and avoid collisions have been explored already [4,22,23,27,31,33]. Using more resources, e.g. multiple links, the reliability of connections can be improved [32]. However, an always reliable connection cannot be assumed and, if no connection is available, movement of an AGV should only be degraded instead of completely stopped. In the following, we detail how monitors for the infrastructure cooperation performance allow to dynamically adjust the forklift's actions to its available information.

2.3 Conflict Detection at Known Blind Corners

At a blind corner, line of sight to crossing vehicles or humans is limited. Known blind corners in a warehouse are critical locations and have already been examined [4,13]. An intersection can only be passed without slowing down, if all conflicts can be reliably excluded. This situation is illustrated in Fig. 1. An AGV approaching an intersection at position 1 has to start braking at position 2 before it is able to perceive the complete conflict area. Otherwise, the AGV cannot stop at position 3 if there is a hidden conflict. When all potential conflicting crossing objects can be excluded, the AGV can accelerate again. The required braking distance and the point at which the conflict area can be sufficiently viewed by the sensors determines a safe speed limit [37] and recreates the behavior of expert drivers in an automotive use-case [25]. In a warehouse, however, walls and obstacles are often closer and forklifts need to decelerate slower [29,34]. Therefore, the presence of conflicts must be available much earlier to prevent the slowdown [4].

For example, at a speed of $5\,\frac{\mathrm{m}}{\mathrm{s}}$, a forklift needs to start braking at a distance d_{brake} of 3.5–6.5 m [34]. While processing inputs, the automated forklift travels $d_{process}$ additionally. The forklift needs to detect the intersection and potential conflicts in the *conflict area*. The time the forklift would take to pass the intersection and the passing human's speed define the size of this area:

$$d_{conflict} = v_{other}(d_{process} + d_{brake} + d_{inter} + d_{fl})/v_{fl}. \quad (1)$$

To avoid a potential collision, the forklift must decelerate, if the conflict area including a margin for the detection (d_{detect}) cannot be cleared. Therefore, using only pure line-of-sight [37], the point of decision is close to the intersection and the forklift already almost stops. When using infrastructure sensors to avoid unnecessary slow downs of an approaching forklift, the sensors mounted at the intersection need at least a detection range with radius

$$R > d_{inter} + d_{conflict} + d_{detect}. \quad (2)$$

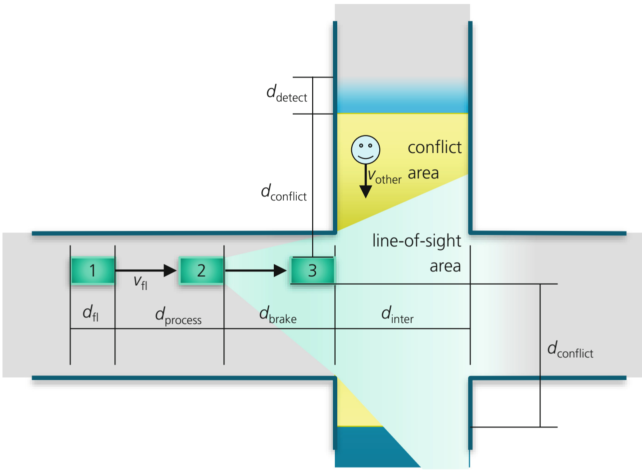

Fig. 1. An automated forklift approaching a blind corner.

Previous work [13] has shown the positive impact on safety and efficiency of automated forklifts at blind corners based on the described conflict detection. Current standards only require personnel detection in the direction of travel. Therefore, industrial trucks may face blind corners at many occurrences. In this work, we examine how this approach can be generalized to reduce risks by automated forklifts for human workers in the entire warehouse, while reducing performance only when necessary.

3 Infrastructure-Cooperative Autonomous Control

In this section, we present our novel approach for safe and efficient automated forklift operation in a warehouse, where human workers might be present. It is based on an architecture [13] that has already been shown to mitigate faults of a safety critical function included using wireless communication, which sporadically might be unavailable or disturbed.

3.1 Infrastructure-Cooperative Autonomous Control Architecture

The infrastructure-cooperative architecture for automated forklifts shown in Fig. 2 covers the core AGV tasks [10] and additional monitoring activities.

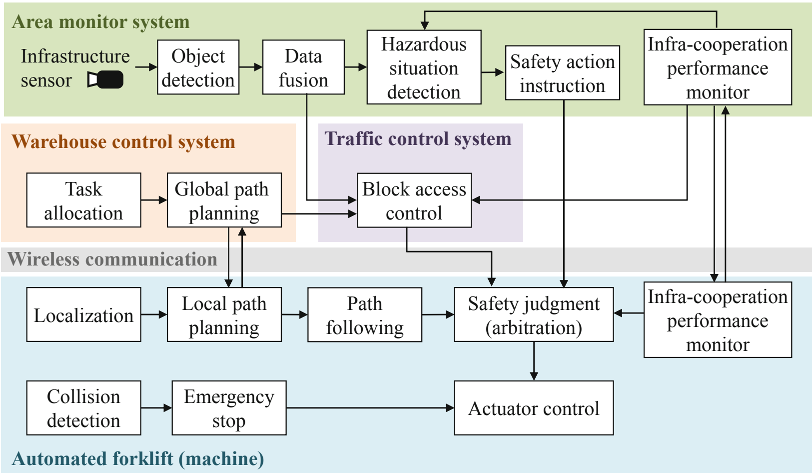

Fig. 2. Infrastructure-Cooperative Autonomous Control Architecture [13]

The **warehouse control system** optimizes the overall operational efficiency by allocating tasks to each forklift and planing necessary routes. The **traffic control system** coordinates the (automated) movement in the warehouse by ensuring that only one machine may enter a certain block at the same time. The **area monitor system** manages the collision risk of machines and workers in the warehouse using available infrastructure sensors. It emits safety actions for safety risks or deviations from rules that are defined as hazardous situation. Safety actions can apply immediately or on a situation detectable by the machine, e.g., an interrupted connection. The **automated forklift** has functions to enable safe and autonomous control, e.g., personnel detection mechanisms using the machine's own sensors required by the ISO 3691-4 [17]. *Safety judgment* ensures safe operation by arbitrating path following, permissions from traffic control, safety action instructions and the system status reported by *infra-cooperation performance monitor*. The monitor detects and mitigates potential hazards introduced by the use of remote information in a safety critical function.

This structure enables collision avoidance in advance and reduces unnecessary deceleration and stoppage of the automated forklift. The operational efficiency can, thus, be expected to be improved. In brief, the proposed architecture ensures safety in three ways:

– block permissions coordinate automated forklifts,
– area monitor safeguards the interaction with humans, and
– emergency stop provides a local backup if remote services are not available.

A key ingredient to ensure safe interaction with human workers is the hazardous situation detection. The following section details how the area monitor can detect such critical situations based on a generalized concept for conflict detection at blind corners.

3.2 Generalized Concept for Conflict Detection

When blind corners are fixed and known, the method described in Sect. 2.3 can detect potential conflicts between a forklift and human workers. However, there are many situations where location of blind corners can rapidly change, e.g., in an area where goods are quickly unloaded from a truck and inspected by humans before they can be moved to a more permanent location. At the same time, interactions between humans and automated forklifts are very likely. Further, as already identified during the discussion of related standards in Sect. 2, any location could be a blind corner for an automated vehicle that only checks for humans in the direction of travel. Therefore, the concept of the conflict area is generalized to assume the occurrence of blind corners anywhere. In the following, we assume that the RTLS has good coverage of the warehouse and its precision is sufficiently considered in d_{detect}.

Conflict detection at known blind corners checks if a forklift can continue at its current speed without interfering with a human at an intersection. This check is performed early enough for the forklift to stop before it enters the intersection and it assumes that this is always safe. A similar check can be performed at any time along the forklifts trajectory. This is shown in Fig. 3. For a constant velocity, (1) can be used to calculate the size of the conflict area. More general, the radius depends on the time ($t_{conflict}$) the forklift needs to reach the checked point and the assumed maximum speed (v_{other}) of human workers:

$$d_{conflict} = t_{conflict}\, v_{other}. \tag{3}$$

For the generalized case, however, stopping might not always be safe and might cause collisions. A trajectory is considered to be safe only, if it ends in a safe position, i.e., if the forklift can stop at its end. Thereby, cases where the forklift can neither stop nor continue safely are avoided. A simple generalized conflict area for a moving forklift is illustrated by Fig. 4. If the area monitor

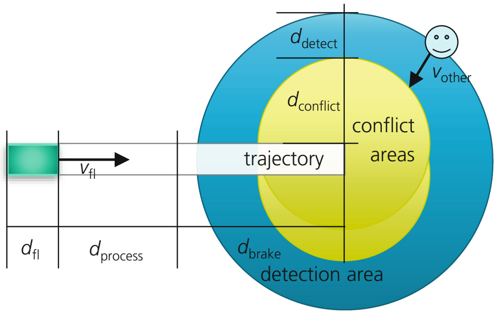

Fig. 3. Generalization of the conflict area.

signals the forklift to brake, the rectangular area denotes the trajectory it needs to safely decelerate. Assuming a maximum speed for human workers, they would only be able to enter the trajectory before the forklift if they are within a conflict area. The conflict areas can be calculated as series of circles along both sides of the trajectory. The resulting conflict areas are marked in Fig. 4. To detect human workers before they enter this area, the detection margin of size d_{detect} is wrapped around the conflict areas. The resulting detection area can be approximated by an isosceles trapezoid and a half circle. Thereby, potential conflicts can be checked quickly. Hazardous situation detection in area monitor will continually check different trajectories for each forklift based on the safety actions it can send to the forklift to avoid conflicts with human workers. Besides stopping and slowing down, maintaining a minimum speed to clear an area before a worker gets closer can also be a possible safety action.

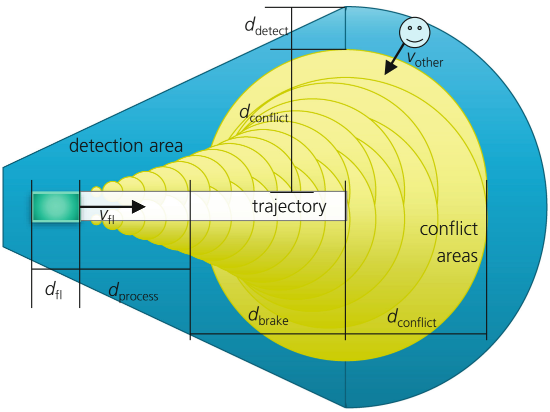

Fig. 4. Conflict and detection area to guarantee the forklift can safely stop.

Forklifts will not only travel in a straight line. For more complex trajectories, waypoints can be placed at turns and other points, e.g. where the forklift's speed will change. Multiple trapezoids with half circles can then be placed along the waypoints, like shown in Fig. 5. For the waypoint marked with the diamond, the time the forklift needs to reach it can be estimated and used to calculate $d_{conflict\_wp}$. The diameter of the half-circle is also used as the length of shorter parallel side of the next trapezoid. Finally, this can be used to avoid checking identical parts of different tested trajectories multiple times.

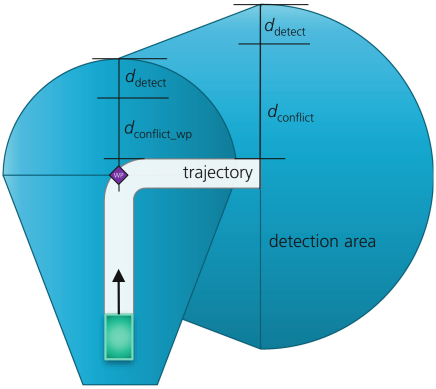

Fig. 5. Detection area for more complex trajectories.

4 Evaluation

4.1 Scenario Description

This section aims for evaluating the effects of the presented concept for safe interaction of industrial trucks and humans on an overall warehouse. For this, simulations including typical warehouse scenes have been created. The evaluation scenario was derived from industrial experiences and existing applications with respect to the warehouse layout as well as tasks of humans and forklifts. Through this, the evaluation scenario leads to various different encounters between automated forklifts and humans. The created warehouse model from bird's eye view is shown in Fig. 6. The warehouse comprises the following main areas: A permanent storage area (blue), two temporary storage areas (grey), and *human-only* areas (green).

Human Workers. In the examined scenario, workers are inspecting goods in the temporary storage areas and, thus, share space with the autonomous forklifts. Within the simulation, human workers' movement is planned along the paths shown by the green and blue lines in Fig. 6. After finishing an inspection cycle, they will directly start the next cycle. In the areas indicated along the paths,

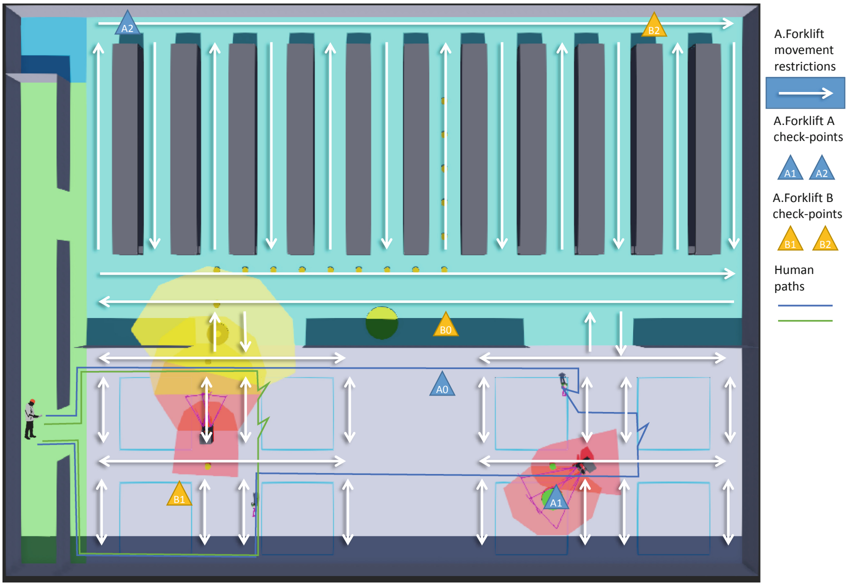

Fig. 6. Webots warehouse model based on the use case derived from common industrial settings (Color figure online)

inspection is simulated by workers performing a small movement cycle. Human workers are moving with constant speed $v_{other} = 1.5\,\frac{\text{m}}{\text{s}}$, which is slightly higher than average walking speed [8]. To create variations in the scenario, the position where humans start their path has been varied by changing the initial time offset. An offset x indicates that the human worker starts at the position it would have reached after x seconds walking along the path. A range of time offsets from 0 to 120 s have been used to cover a wide range of possible interactions between autonomous forklifts and human workers, resulting in 60 simulation runs for each safety concept and for each scenario.

Human-Driven Forklifts. To test the safety in the presence of faster moving objects, human-driven forklifts have been implemented moving along predefined paths. One human-driven forklift was added to each temporary storage area. The implementation is similar to that of human workers, i.e., collisions with automated forklifts are detected but have no other impact on the simulation. The predefined paths simulate retrieving goods from a nearby truck and placing them in one of the marked areas.

Automated Forklifts. The simulation assumes a rated speed of $5\,\frac{\text{m}}{\text{s}}$ and a value of $3\,\frac{\text{m}}{\text{s}^2}$ for brake and acceleration. They are tasked with the transport of goods from the temporary storage area to permanent storage and vice versa. This is simulated by having forklifts move between checkpoints in each area. Navigation options available to automated forklifts are indicated by white arrows. The arrow depicts the direction the forklift may travel. Planning and coordination between forklifts is done using an adapted version of a cloud-based control for cars in a parking area [14]. Therefore, the cloud will plan waypoints for each forklift and provide it with a permission stating how far it may proceed. For permissions, the navigation options, i.e., the shown arrows, have been split into blocks of approximately $9\,\mathrm{m}^2$ size. The permissions ensure that only one automated forklift will occupy a block simultaneously, thereby, preventing collisions between automated forklifts.

Safety Concepts. For safe interaction with humans, we evaluated four safety concepts (SC) to compare distinct safety considerations in a warehouse: SC_0 uses the rated speed of the forklift anywhere, unless its local sensors detect a human. SC_1 uses the hazardous zone speed for the temporary storage area and the rated speed otherwise. SC_{slow} and SC_{stop} use the hazardous situation detection as described in Sect. 3.2. The checked areas can also be seen in Fig. 6 around the forklifts. SC_{slow} uses the safety action *slowdown* but will send *stop* for the closest segment. SC_{stop} always uses *stop*. To challenge the robustness of the approach, the algorithm only checks for conflicts every 0.3 s. For any safety concept, local emergency stop of the automated forklift is active and will cause the forklift to stop.

4.2 Metrics

Safety. The primary goal or our introduced safety concepts is to prevent collisions – even though a human worker is violating safety guidelines and not paying attention to his surroundings, e.g., walking into a forklift that is driving according to its safety rules (i.e., follows speed and acceleration constraints, drives along calculated waypoints). Thus, we analyze the number of collisions as main indicator. For implementation reasons, human workers strictly follow their programmed path in the simulation, e.g., they can walk into a slow moving or stopped forklift. Thus, we consider a collision to be safely avoidable in reality, if the forklift reduced its speed to below $1.2\,\frac{\mathrm{m}}{\mathrm{s}}$ and stopped rotating at least 0.25 s prior to the collision. In these cases, it is assumed that a real human would in general not walk into the forklift. All other collisions are considered unsafe in our evaluation, where we distinct front collisions due to their high severity. In case of front collisions, the tips of the fork make first contact with the human, which is considered to be most severe. Simulation continues without interruption when a collision is logged, i.e., there is no physical impact and collided entities continue their tasks.

Performance. The secondary goal of introducing the novel concepts is to avoid an unnecessary impact on the performance of the system. To compare the performance of the different concepts, the distances which the forklifts traveled have been measured and recorded. For easier comparison, the performance drop is calculated. It is relative to results of SC_0, which is expected to provide the best performance out of all concepts.

4.3 Results

Early Results. An initial, simple approach for hazardous situation detection that checked only the generalized conflict area shown in Fig. 3 enticed with potential but provided unsatisfactory results. Parts of conflict areas were not checked for human presence – especially during turning – which caused many severe collisions. Those experiments, nevertheless, helped to develop the final approach that would minimize the area of detection, while assuring the complete coverage of possible collisions.

Results. Table 1 presents the results for simulations of 2 unmanned forklifts, 2 to 4 human workers (HW) and up to 2 human-operated forklifts (HFL). Collisions listed in the table are considered hazardous, i.e., the speed of an autonomous forklift was higher than the safe speed of $1.2\,\frac{\text{m}}{\text{s}}$. Without implementing human behavior of avoiding a safely stopped automated forklift, which was out of the scope of this work, all collisions logged when an autonomous forklift was moving at slow speed or slower, are considered as not severe and easily avoidable in real situation. For validation purposes, times of human interacting with completely stopped forklift were still logged.

SC_1 by definition will never cause an unsafe collision because in this scenario, autonomous forklifts are never moving faster than slow speed in the area shared with human workers. SC_{slow} and SC_{stop} also allow to avoid all unsafe collisions. In addition, SC_{stop} allows to completely stop before almost all collisions, i.e., no action of collision avoidance is required from human workers or drivers of manned forklifts. This is a significant improvement compared to SC_0, which shows several or more unsafe collisions, depending on the individual scenario. SC_1 causes almost 7% performance decrease in all scenarios, due to often unnecessary slowing down. SC_{slow} ensures no collisions and decreases performance only by about 1 to 1.6% for scenarios with human workers only. SC_{stop} also ensures no collisions, but reduces performance by 3.2 to 6.4%, depending on the scenario.

When more human workers are introduced, the number of collisions will likely increase and performance drop, because there are more potential interactions between unmanned forklifts and humans. The number of unsafe collisions, increases much more when SC_0 is used, while SC_1, SC_{slow}, and SC_{stop} still avoid all collisions. In the examined scenarios and with the improved conflict detection implemented by the cloud, SC_{slow} and SC_{stop} provide significant improvement of safety compared to SC_0, regardless of the number of human workers in the warehouse. SC_{slow} provides also better performance than SC_1 without compromising safety. On the other hand, SC_{stop} can assure not only severe collisions avoidance, but not collisions at all – the price would be decreased performance. The performance measured as traveled distance decreases with the number of human workers – the more interactions between humans and forklifts, the more time forklifts must perform safety actions and slow down or brake.

The number of collisions significantly increases, when manned forklifts are included in the simulation – but only when SC_0 is used. Again, SC_1, SC_{slow},

Table 1. Simulation results with number unsafe collision, as well as distance in meters traveled by the forklifts summed over all scenarios with the matching amount of human workers (HW) and manned forklifts (HFL). Performance drop is given relative to SC_0.

Scenario			Safety	Performance	
#HW	#HFL	SC	#collisions	Total [m]	Drop [%]
2	0	0	2	31,597	0.0
2	0	1	0	29,522	6.6
2	0	Slow	0	31,275	1.0
2	0	Stop	0	30,583	3.2
3	0	0	2	31,394	0.0
3	0	1	0	29,405	6.3
3	0	Slow	0	30,947	1.4
3	0	Stop	0	30,280	3.5
4	0	0	4	31,085	0.0
4	0	1	0	29,165	6.2
4	0	Slow	0	30,582	1.6
4	0	Stop	0	29,093	6.4
2	1	0	42	31,599	0.0
2	1	1	0	29,522	6.6
2	1	Slow	0	30,596	3.2
2	1	Stop	0	27,851	11.9
2	2	0	67	31,601	0.0
2	2	1	0	29522	6.6
2	2	Slow	0	30,252	4.3
2	2	Stop	0	21,294	32.6

and SC_{stop} provide improved safety in comparison. Costs for the higher safety are lower performance, even lower than for SC_1, in case of SC_{stop}. This is a result of many interactions between unmanned forklifts, manned forklifts, and human workers. However, SC_{slow} allows mitigating these costs.

Discussion. The results show that fast moving manned forklifts might require a different or more refined approach than human workers, who are much slower than vehicles. In turn, movement of vehicles is much more limited by physics, and therefore, some potential interactions could be excluded by reliable predictions. In all executed scenarios, the cloud service checks for conflicts every 0.3 s only. Especially when including fast moving objects like manned forklifts, a higher rate of updates in the cloud could improve this situation. Moreover, depending on the use case, it may be beneficial to limit the maximum speed of manned forklifts to improve the performance of unmanned forklifts. In our experiments, we assumed the same maximum speed for all kinds of forklifts ($5\,\frac{\mathrm{m}}{\mathrm{s}}$).

As SC_{slow} and SC_1 already avoid all unsafe collisions, the results presented in Table 1 indicate no clear benefit of using SC_{stop}. However, this approach could be beneficial, e.g., to provide safety if untrained personnel can enter shared areas or to help in a transition phase when automated forklifts are firstly introduced. In this case, the systems takes over responsibility that humans cannot collide with a moving forklift. With few humans working in the same area, we observed a performance impact less than or comparable to that of SC_1. Because humans did not avoid collisions in our simulation (even when safely avoidable), we could examine the speed of automated forklifts in these incidents. As expected for SC_{stop}, the automated forklift had already stopped and humans collided with a then static object. Even if just at slow and safe speeds, the forklift was still moving for most incidents of SC_1 and SC_{slow}. Further simulations for cross-validation purposes with additional humans walking between random waypoints in the shared area presented a similar performance drop distribution.

Summary. The results of the simulations clearly show that areas shared by autonomous vehicles and humans or human-driven vehicles require novel approaches to assure safety and to keep the performance on satisfactory level. In this case, safety cannot rely on sensors and systems embedded into vehicles only. Additionally, it is advantageous that modern mobile robots are often already connected to cloud-based systems, e.g., for task planning and navigation purposes. Using infrastructure sensors and sharing information about location of humans makes a system more complex, but it also allows avoiding dangerous collisions while maintaining high system performance.

5 Conclusion and Outlook

This paper examines the interactions of automated forklifts and human workers in shared areas of a warehouse to increase the safety in these areas. Based on an architecture that includes infrastructure sensors, we introduce a novel concept to identify potential conflicts in the movement of automated forklifts and human workers while having minimal impact on performance. The presented results for interactions in the entire warehouse confirm the first observations made for known blind corners [13]. It is clear that relying solely on the forklift's sensors either poses a high risk to human workers if the forklift does not brake as a precaution (SC_0), or suffers a significant drop in performance (SC_1). When the information from infrastructure sensors is added (SC_{slow}), the decision to slowdown can be made dynamically, reducing the impact on performance. Still, a small risk remains if a slowly approaching automated forklift is ignored. However, instructing forklifts to unconditionally stop for nearby humans (SC_{stop}) will lead to unnecessary waiting times.

In the future, the prediction of human workers could be improved when more reliable information is available, for example by recognizing people's intentions and awareness. Switching between the safety concepts can adapt the system to the personnel present in the shared area.

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