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Trajectory Prediction of Workers to Improve AGV and AMR Operation based on the Manufacturing Schedule

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Abstract

In semi-automated manufacturing, an increasing amount of intelligent mobile robots operate in close proximity to human workers. Considering future positions of humans allows to further improve the efficiency in terms of throughput of Autonomous Mobile Robots (AMR) and Automated Guided Vehicles (AGV). The longer the prediction horizon, i.e. the more position values of humans can be predicted in the near and distant future, the more a robot can adjust its route accordingly and optimize the process. This paper discusses the challenges of human motion trajectory prediction in manufacturing and presents a schedule-based approach that uses real-time schedule data obtained from Manufacturing Execution Systems (MES). Schedule-awareness in human motion trajectory prediction extends semantic mapping approaches and effectively reduces the number of probable destinations by considering which process steps are next for the currently produced goods. With a reduced set of destinations, the performance of forward-planning trajectory prediction can be improved. For evaluation, a commercial MES is used together with an Ultra-wideband-based Real-Time Locating System (RTLS) for obtaining position data of humans. On this basis, a naive Bayes classifier utilizes MES-schedule and real-time position data to predict human motion intentions. Abstract activity modeling ensures that only a few training data sets are required for deployment, thus making this approach suitable for rapidly changing manufacturing environments such as in flexible manufacturing.

Keywords: Trajectory Prediciton; Human Workers; Operator; Context; MES; RTLS, AGV; AMR

1. Introduction

Due to major advances in the robustness of Autonomous Mobile Robots (AMR) and Automated Guided Vehicles (AGV), their deployment is predicted to grow rapidly [1–3]. The achievable transport throughput falls far short of the performance of fixed systems such as conveyor belts [4], but mobile robots address a different user group with high demands on flexibility and easy integration into semi-automated brownfield manufacturing plants. But especially in mixed operation, where the traffic area is shared by humans and mobile robots, the transport throughput is particularly low, as robots are only allowed to move much slower than technically possible due to very strict safety requirements [4].

The human motion prediction approach discussed here contributes to better consideration of the environment in robot control, also referred to as human-aware navigation [5]. By using additional environmental, robot-external sensing and algorithms for trajectory prediction of humans, robots can better understand human behavior and take it into account in their path finding [3, 6]. In addition to eliminating congestion or blockage situations between human workers and robots, it is also conceivable to use this approach to increase the average as well as maximum speed of mobile robots while still maintaining a high level of safety and worker well-being.

The addressed **research question** of this paper is: How can the underlying motivation of a human worker's movement be better understood? The described manufacturing-schedule-

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based approach is based on the analysis of the current order situation, which allows conclusions to be drawn about the current and future tasks of a human worker. This knowledge is then used to draw conclusions about necessary position changes, i.e. the motivation of movements.

This paper addresses manufacturing and the presented schedule-based approach uses data from a Manufacturing Execution System (MES). The approach can also be applied to warehousing and used together with Warehousing Execution Systems (WES) or Warehouse Control System (WCS).

The remainder of this paper is structured as follows: Section 2 is dedicated to the discussion of human motion trajectory prediction approaches. In Section 3 the schedule-based approach is proposed and the realization requirements are discussed. The Festo MES4 forms the basis for the realization that was used for evaluation, which is presented in Section 4. Finally, conclusion and outlook follow in Section 5.

2. Basics and Related Work

2.1. Trajectory Prediction of Humans

Trajectory prediction involves predicting the movements of <u>other</u> autonomous units. Trajectory prediction is often used to improve the trajectory planning of mobile robots. Trajectory planning is about determining a possible movement trajectory for a robot or ego-vehicle.

Trajectory prediction, as illustrated in Figure 1, is useful for all location-dependent optimization problems [7]. The earlier and the more accurately an automated system senses its environment, the more optimization scope there is. In the problem domain of manufacturing, this applies to scenarios with many autonomous movements, e.g. especially in job shop and matrix production scenarios. Note that trajectory prediction is relevant when there are autonomous mobile systems in the vicinity. In a fully automated human-less factory, trajectory prediction is for example only necessary if there are no interfaces between mobile robots from different manufacturers. This could occur due to vendor dependency reasons but is unrealistic from a technical and research perspective. Therefore, a much better example of a real autonomous system without digital interfaces is a human. For human workers, it requires trajectory prediction methods to enable automated systems to reason about future locations of the autonomous human workers in a factory [6].

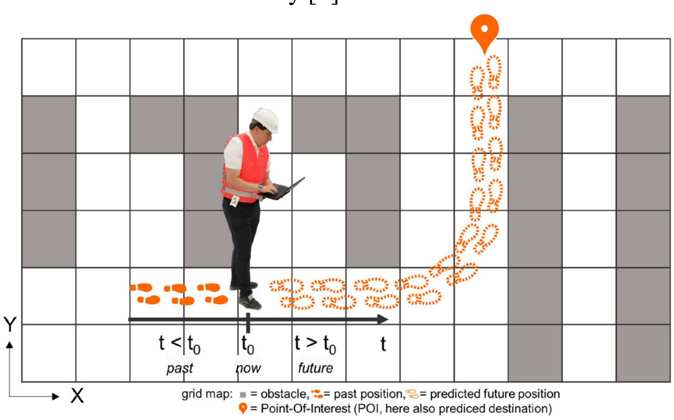

Figure 1: Trajectory Prediction of a Human Worker

The prediction of a trajectory represents a data processing procedure, from inputs a prediction is generated as output. What form inputs and outputs have is handled differently. In any case, the location and often also past location values are required as input [7]. The measurement of the spatial location of humans can be done by different sensor technologies. Commonly, calibrated cameras are used to determine the location, direction and speed of movement [7]. Real-Time Locating Systems (RTLS), which are increasingly used in manufacturing, are a possible alternative [6]. RTLS are considered to be the Swiss army knife in the field of flexible and networked industrial automation and data-driven optimization, since highly dynamic position data of products, tools, machines and human workers contain a lot of information about the current production process [8, 9].

The output, a predicted trajectory, is usually a tuple series of {timestamp, predicted motion state} [7]. The motion state contains information about the predicted location and optionally further information like the velocity or the direction of a motion. For the description of the location prediction it is usual to give coordinates as well as information about the uncertainty, often probability distributions are specified [7].

2.2. Planning-based Trajectory Prediction approaches

Trajectory prediction is possible using so-called *planning-based methods* that are a sub-category of trajectory prediction approaches. The approach discussed in this paper is an enhancement to planning-based methods, but this should not be confused with trajectory planning approaches. Trajectory planning handles the problem of determining a motion trajectory for robots or ego-vehicles. Planning-based trajectory prediction is about predicting the movement of <u>others</u>.

In research area of trajectory prediction, surveys [7, 10–12] contribute to the harmonization of terminology. Closely related is location-, position-, destination- and route-prediction.

According to [7], there are three main categories of trajectory prediction methods. *Physics-based approaches* reproduce the conservation of momentum at their core and are thus very lean and efficient white-box models, but allow only very short prediction horizons [6, 7, 13, 14]. Along with planning-based approaches, *pattern-based approaches* are very popular today. They are black-box models that use machine learning methods to derive predictions from data [7, 15–17]. *Planning-based approaches* are based on the assumption of a goal-oriented, rational movement behavior of humans [7, 18–22]. The better the motivation of a movement can be understood, the more precise the prediction can be. Approaches from this area focus primarily on the area of human motion prediction with wide prediction horizons. Realizations are often a hybrid of white-box models and the use of machine learning for parameter optimization. In addition to the state of motion, maps with information about static obstacles or so-called semantically extended maps with additional information about Points-Of-Interest (POI, e.g. doors, working spaces, etc.) are used to enable modeling of rules like “avoid obstacles” or “follow a path”. In addition to static contextual cues, modeling social forces (rules like “stay together”) can improve trajectory prediction. [7]

As discussed in [7, 10–12], the applications of predicted trajectories are mainly in the fields of automotive and robotics. In both fields, the objective is to understand the movement of humans as precisely as possible in order to obtain more time for action in the system control to achieve optimal results. In robotics, the focus is on path optimization that requires predictions with wide prediction horizon. Here, trajectory prediction is mostly used in parallel with existing safety routines. In the area of manufacturing, the focus is on improving human-robot collaboration with mobile robots [6, 19, 23] and robot arms [14, 20, 24].

2.3. Trajectory Prediction with Modeling of Action Intentions

Planning-based trajectory prediction methods are based on the assumption that humans behave rationally. Current methods are often limited to the replication of simple action rules such as following marked paths, avoiding obstacles, or moving together as a group [7, 15–18, 21]. In psychology there are more profound models for the derivation of action intentions, which are based on the work of Atkinson, Fishbein, Ajzen, Kuhl and Bratman, among others. Analogous to the planning-based trajectory prediction methods, the key is the assumption of a predominantly rational behavior [25]. Important for artificial intelligence research and engineering applications in general is the belief-desire-intention(-action) theory developed by Bratman [26]. The action of a human, such as the movement of a human, is observable and measurable. The intentions for an action and the reasons that lead to a movement are not directly measurable but can be modeled. A variety of modeling depths is possible, ranging from modeling of basic intentions, such as avoiding collisions with obstacles [7, 18], up to sophisticated desire-fulfilment intention modelling [7, 19, 22]. In the literature, the term "intention" is used for all kinds of planning-based trajectory prediction approaches. The approach discussed in this paper uses assigned tasks data for intention prediction. This information is vastly available in manufacturing via Manufacturing Execution Systems (MES). Such systems control and document the flow of goods within factories.

3. Manufacturing-Schedule-based Trajectory Prediction

As discussed in [6], the unlocking of significant optimization potential in the area of mobile robotics also requires the most anticipatory sensing of the dynamic robot environment possible. In semi-automated manufacturing, moving workers are part of the environment of mobile robots must appropriately consider by them.
The in this publication discussed schedule-based approach represents an enhancement to existing planning-based-methods that focus on a wide prediction horizon [7]. The basic assumption of planning-based methods that humans act in a goal-oriented and rational manner is also valid in manufacturing, but here is another decisive advantage. Existing methods from the field of automotive and pedestrian prediction model the rationality of pedestrians in their goal fulfillment as a cost function [7]. However, due to the anonymity between traffic participants, no in-depth personal data can be used except for the current state of movement as well as basic rules such as “preference to marked paths”. As discussed in Section 2.3, mostly basic intentions are modeled and used so far to improve the quality of trajectory predictions and movement intentions are modeled and understood in a very rudimentary way. In manufacturing, on the other hand, human workers are not anonymous strangers, and their goals are known based on the assumption that human workers movements are heavily influenced by their current tasks. Specifically, current orders and assignments are digitally managed by the MES. The use of such information about orders and assignments represents a deeper modeling of sophisticated desire-fulfilment intentions that is still justifiable under labor law. The schedule-based concept therefore makes it possible to further improve the quality of trajectory predictions by providing a more accurate understanding of why someone is moving.

The concept is shown in Figure 2. In addition to the current positions of workers, a semantically extended map is also required as input. Furthermore, in order to better capture the reasons why a movement is necessary, schedule information from the MES is evaluated. The usual work shift and break times are also known to the system.

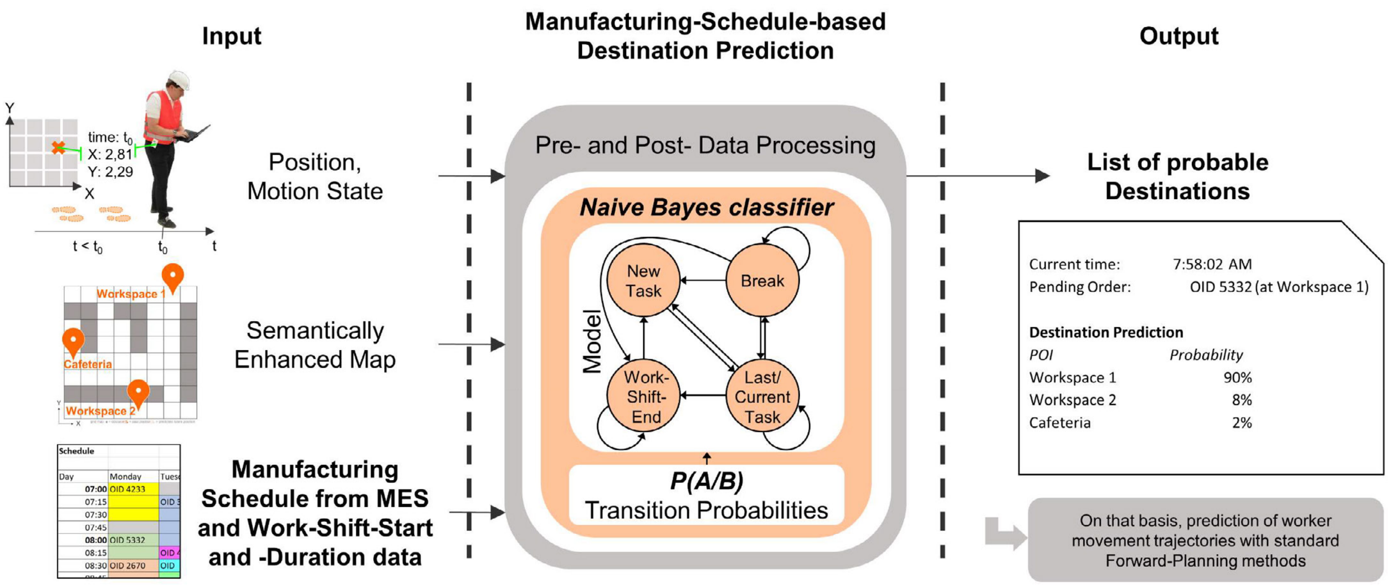

Figure 2: Manufacturing-Schedule-based Destination Prediction

With perfect adherence to a planned schedule, the destination of every human worker movement could be predicted without uncertainty. However, humans are characterized by their autonomous behavior and their ability to intelligently extend, shorten, interchange, etc. tasks and assignments. As a result, planned schedules are never fully adhered to and the concept must be capable of dealing with uncertainty when considering schedule information for improved trajectory predictions.

The core of the concept of schedule-based destination prediction is therefore a naive Bayes classifier for modeling the uncertainty regarding the movement destination of human workers. As illustrated in Figure 2, the naive Bayes classifier is composed of the model and the knowledge base. The knowledge base includes all transition probabilities, which can be either manually specified or learned from data. The learning process can be frozen if the results are satisfactory, or it can be continued continuously at runtime. The naive Bayes classifier is selected for its ability to combine white-box modeling with black-box machine learning. As the state space is limited, the complexity is still manually manageable. If training data are not yet available, this classifier can be also used on the basis of expertly selected transition probabilities. A more general neural network-based classifier is a valid alternative that requires much more training data before it is operational.

The knowledge base stores the conditional transition probabilities of the naive Bayes classifier. Figure 2 shows the model built on top of this describing all possible transitions. The intuitive approach to transition modeling is to consider the semantically extended map and model each Point-Of-Interest (POI, e.g. each workspace) as a separate node with transitions between all nodes. However, this leads to two problems. On the one hand, this results in a large number of nodes and a correspondingly large number of transition probabilities must be determined. Furthermore, changes in the layout of a factory that lead to the creation of new and the deletion of old POI are a problem. In flexible semi-automated manufacturing that is addressed here, workflows frequently change. As a result, the positions of the POI as well as the transition probabilities change, the naive Bayes classifier would have to be trained anew each time.

To counteract this and thus increase practical relevance, the model shown in Figure 2 is therefore used. Instead of modeling every POI as a node, we abstract between only four nodes: *Work-Shift-End* and *Break* follow the logic of modeling POI as node, for those two for example the door to the break room or the changing room. In contrast, *Last/Current Task* and *New Task* abstract all the other POI. Instead of modeling each workstation as a separate node, however, a distinction is only made as to whether the current activity is being continued or whether it is being terminated and a new activity is being started. The resolving of the activity to the location is done using the information of the Manufacturing Execution System, which provides data on the schedule of the production process as well as the allocation of resources and thus the location.

Based on the known time for work start, the known time periods work shift and break, the production schedule, the location of Points-Of-Interest and the transition probabilities, the destinations of human worker movements are predicted using the naive Bayes classifier. Consideration of other contextual information is possible and is discussed in Section 5. Knowledge about the probable destination of a movement is a big step towards trajectory prediction as from there on forward-planning methods, that are based on pathfinding algorithms, can be used to determine and predict efficient routes between the current location and the predicted movement destination. The more accurately the movement destinations are predicted, the more confident predictions about the actual movement of human workers can be provided.

4. Realization and Evaluation

For any kind of trajectory prediction current position data is required. Which technology provides position data is secondary, but realistic for the addressed problem domain of manufacturing is the use of an Ultra-wideband-based (UWB) Real-Time Locating System (RTLS) [8, 9]. This technology also provides via a MQTT-interface the position data in the context of this publication [27]. The use of the schedule-based destination prediction method also requires a forward-planning algorithm for trajectory prediction. An [28]-oriented A*-based approach is used, which is implemented in Python. The forward-planning algorithm requires the current position and a single or a set of movement destinations for trajectory prediction.

The schedule-based destination prediction enhancement discussed in this publication then provides better predictions regarding the destination of a human movement. Therefore, additional schedule data is needed, which is obtained from a Manufacturing Execution System (MES). All of the required software is realized in Python as a Django web application which is run on a local server-PC.

The evaluation was carried out on the one hand data-based and on the other hand with real-time data during tests in the IAS Cyber-Physical Production Lab that is shown in Figure 3. As already described in [29], modules of the Festo Cyber-Physical Factory platform are installed there. In total, there are five workstations. Each workstation is controlled by a PLC. The entire production system is controlled and managed by the Festo MES4 [30], which provides an SQL-based interface for accessing schedule data.

The schedule-based destination prediction module therefore receives current information via MQTT and SQL. Non-variable information such as work shift times, break times and the semantically extended map of the lab are stored in a PostgreSQL database. The naive Bayes classifier is implemented in python and embedded in a Django environment. The request for a trajectory prediction is first answered with an uncertain prediction of possible destinations before the full trajectory is predicted using forward-planning methods. The uncertain prediction of possible destinations uses the map of the lab, the data from the Festo MES4, and the real-time position data from the UWB RTLS during testing in the IAS Cyber-Physical Production Lab. To reduce temporal uncertainty, it is assumed that trajectory predictions are only requested and calculated <u>after</u> the movement of a worker started. The starting time of a movement is not predicted, this requires more information e.g. from task progress monitoring.

When evaluating the destination prediction, the focus is on the achievable reduction of uncertainty regarding the actual destination of human movement. The more precisely the destination can be predicted, the better forward-planning-based trajectory predictions will be. The prerequisite is the definition of a set of Points-Of-Interest (POI) on the semantically extended map of the laboratory. For better comparison, "schedule-based destination prediction" is compared with "no destination prediction" and "motion state-based prediction".

With "no destination prediction", no POI can be excluded for forward-planning; trajectories must be calculated to all POI-defined destinations. Usually the number of POI is limited and the probability that one of the predicted trajectories is correct is equal or less to one divided by the size of the POI set, the uncertainty is at maximum.

A destination prediction can also be computed purely on the basis of the current motion state. The prerequisite for this, however, is real-time location data with little noise for the most accurate possible representation of the motion state. In addition, a movement must already have started in order to be able to make predictions about the destination. The extent to which the number of possible destinations can be narrowed down with the motion state-based prediction of the destination depends strongly on the individual layout of the laboratory (or factory). This can work well for layouts with POI that are far apart from each other, but it does not work if many POIs are close together as then all POI represent reasonable destinations.

The concept of schedule-based destination prediction presented in this paper is independent of the individual layout of the laboratory (or factory). In contrast to the prediction depending purely on the movement state, it is also possible to consider uncertainty regarding the consistency of a decision for a movement destination. During evaluation in the IAS Cyber-Physical Production Lab, four POI are considered as shown in Figure 3. The result diagram in Figure 3 illustrates that without destination prediction the average prediction reliability is 0.25, one to the size of the POI set. The pre-trained schedule-based destination prediction achieves a much better prediction reliability of 0.8 by considering schedule data from the MES. The prediction reliability describes the average probability of the most likely predicted movement destination. With four possible movement destinations, 0,25 means maximum uncertainty, and 0,8 means that it is possible to really predict a certain destination thanks to MES schedule-data. By taking additional data sets into account, the schedule-based destination prediction learns over time even better how human workers usually decide. If decisions are always non-rational, i.e. if the schedule is always deliberately disregarded, the prediction reliability drops. This is an indication of modeling error, e.g. of the absence of important influencing factors in the modeling of human movement motivation. However, if the modeling is correct and rational decisions are made, the prediction reliability increases.

5. Conclusion and Outlook

High-precision trajectory prediction is an enabling technology for natural human-robot collaboration, where robots can not only observe but also anticipate behavior. The prediction of movement destinations helps robots to understand human movement. This is beneficial in scenarios where mobile robots such as AMR or AGV and humans maneuver closely together, e.g. especially in job shop and matrix production scenarios.

Unlike to other application areas of trajectory prediction, human workers in manufacturing are not anonymous strangers and their movements are usually directly motivated by their tasks. The manufacturing-schedule-based trajectory prediction approach discussed in this paper is an intuitive method to answer the research question of how to better understand the motivation behind the movements of a human worker. Schedule data from Manufacturing Execution Systems (MES)

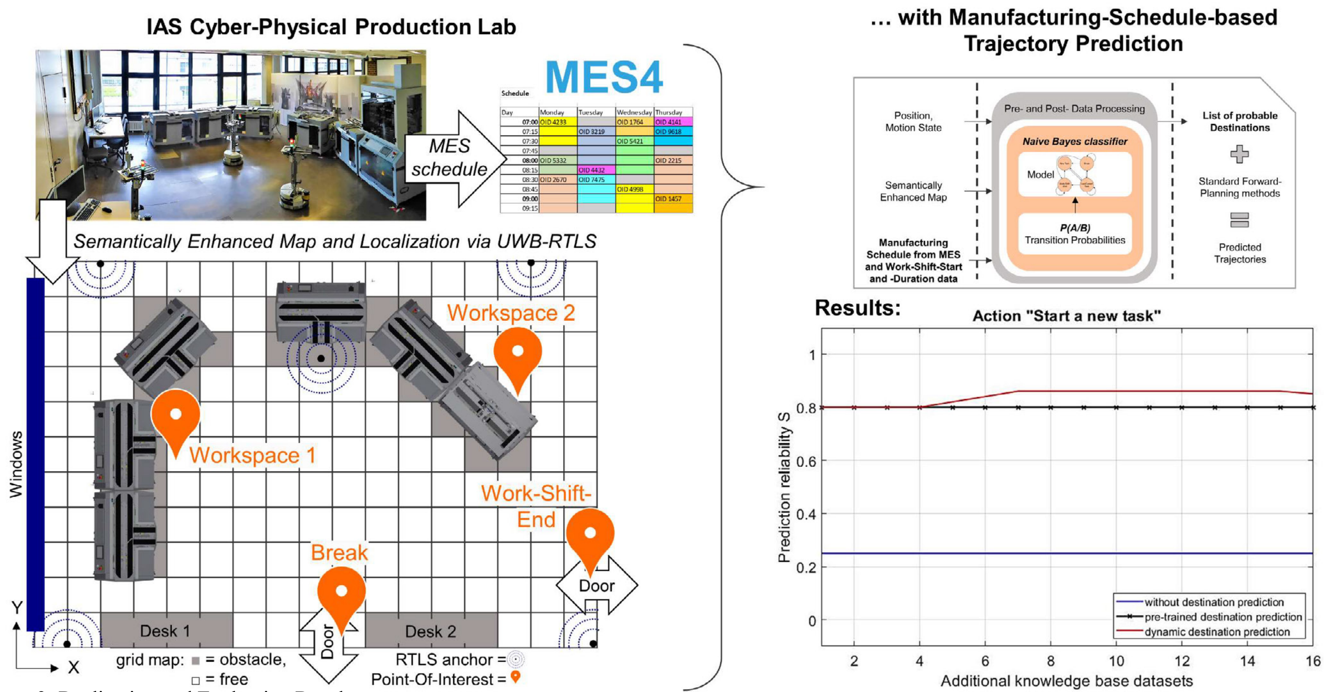

Figure 3: Realization and Evaluation Results

is useful for modeling rational human movement behavior motivated by order and assignment fulfillment. And better predictions of movement destinations increase the quality of trajectory prediction.

For implementation, interfaces to a Real-Time Locating System (RTLS) and to an MES are required to obtain real-time data about the current position of a worker as well as his or her current and next tasks. Since MES and RTLS are widely used in manufacturing, the presented approach has a high practical relevance as it is an enhancement that can be easily integrated.

In manufacturing, trajectory prediction methods become important due to the increasing use of Automated Guided Vehicles (AGV) and Autonomous Mobile Robots (AMR). The very low speed of mobile robots in semi-automated scenarios, where robots operate in close proximity to workers, is currently still necessary to ensure safety. With significantly improved situation understanding, AGV and AMR can move faster and smarter and thus improve their operation efficiency. The schedule-based approach discussed in this paper improves the situation understanding of robots by enabling them to better understand the motivation behind a human movement.

Future work will address the use of additional contextual information to more precisely model the motivation for movements and especially the reasons for not adhering the planned schedule. Therefore, it is promising to take person-related data into account. Approaches from the field of Human-Digital Twin [31] promise a possibility for a data protection-compliant realization. For the reuse of context information, context middleware is suggested [32].

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