Towards Optimization of Manufacturing Systems using Autonomous Robotic Observers

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Abstract
The optimization of existing manufacturing systems is a challenging and highly complex task, requiring high-quality information about the current system. Currently, acquiring such information involves tedious and to a large extend manual work. In this paper we present an ongoing joint project effort bringing together cognitive robotics and planning and control of manufacturing systems to create a closed-loop process that allows for automatic optimization of the observed manufacturing system. Our robot-based approach is minimally invasive to an existing system and applicable in a broad range of logistic scenarios, enabling economic optimization of a wide range of manufacturing systems.

Keywords:
autonomous robots, logistic system optimization, cognitive approach, RFID localization

1. Introduction

An essential factor for analyzing and optimizing logistic systems is the availability of reliable information about the system state and its dynamics. Advanced operational control also relies on up-to-date system information about type, quantity, location, and quality of handled commodities and other resources of the system.

In the following sections we concentrate on the field of warehouse logistics, that is, how to optimize storage areas before/after production/assembly lines, or material supply areas in a manufacturing system. Current approaches to obtain information necessary for an optimization process of such systems require rather severe changes to the warehouse under investigation and involve mostly manual work to acquire the information necessary to start the optimization. Due to the automated data acquisition and analysis process it is also possible to economically collect data for long time spans.

In the project presented in this paper we investigate a new approach of acquiring system information in a minimally invasive and automated manner, that is, without interfering with existing processes. For this purpose we employ a mobile robot platform as a system observer. As any observer only has a limited view, it is not possible to assess up-to-date information of changing or dynamic systems. So the challenge of such a system observer is to collect the *essential* information and to reconstruct missing pieces using background knowledge whenever possible. In our project we employ methods from *spatial cognition* [1] to develop an intelligent robotic observer that *understands* the logistic processes observed. This yields an abstract model of a logistic system and its processes. Additionally, we need to develop means to empower subsequent logistic analysis to exploit abstract process information and create a closed-loop process that allows for an automatic optimization of the observed logistic system.

2. Scenario

In this paper we concentrate on the field of warehouse logistics, in particular on so-called *chaotic* or *random storages* [2]. Chaotic storage systems have no fixed assignment of storage bins to specific (types of) goods. For storage operations it is usually the responsibility of the warehouse operator to find appropriate storage bins. Warehouses using the principle of random storage provide fast and flexible operation for storage and retrieval of goods as well as good utilization of the storage space available. The high degree of dynamics present in chaotic storages complicates short-term inventory control and management. Thus, for operating random storages, IT support to link goods with their current storage bin is essential.

The initial situation we consider is as follows: A company plans the optimization of its warehouse where palletized goods are stored and handled with forklifts. The warehouse uses chaotic storage; decisions where to store or restore goods are made by the forklift drivers and entered in a warehouse management system manually later on. Such a procedure is error-prone and thus has to be improved. We aim at identifying optimization potential in the storage space required and in the times of putting goods into stock and retrieving them from stock. A solid model of the warehouse and its current processes allows a logistic expert to optimize its operative processes, for example, by adapting the layout of the storage or by modifying storage policies (see [3], e.g.).

3. Approach and Methodology

3.1 RFID-based Identification of Goods

As a technical solution, the introduction of RFID (radio frequency identification)-based technologies [4] promises a significant improvement of process transparency and in general allows for automatic data gathering in the quantity and quality required. Objects to be detected can be equipped with cheap, passive tags which can be uniquely identified. Currently, however, RFID based systems require extensive organizational and technological changes: Processes are transformed to so-called *guided processes*, and the flow of materials has to follow predefined points (e.g., through RFID gates). Alternatively, it is possible to use permanently localizable floor-borne vehicles equipped with RFID readers [5]. However, this approach requires all storage operations to be performed with these special vehicles, and the

Figure 1: A Pioneer-3 mobile robot platform equipped with a 3D laser range unit in an experimental storage environment. RFID readers are not mounted to the platform in this picture.

approach is not robust with regards to undetected operations. Any stock movement that is performed without these vehicles or erroneous manual input of storage bin usage results in inconsistent data in the warehouse management system.

In our project we employ a mobile robot platform (see figure 1) that is equipped with a RFID reader for minimally invasive identification and localization of goods. This allows identification and localization of goods (by triangulation from measurements taken at different positions). Furthermore, the approach does not rely on adherence to handling requirements.

3.2 Using a Mobile Robot Observer

In contrast to stationary RFID readers, a mobile system is able to estimate the position of RFID tags in space reliably by combining observations from different positions [6], [7]. In principle, this allows us to build a map that registers all goods. However, we need to take into account the dynamics of the underlying process: Observing the same good at a different position might be explained by a faulty measurement or by movement of the good. Obtaining maps in dynamic environments is a challenging problem studied in the field of autonomous mobile robotics and a solution to it requires differentiating between moving objects and objects that are (currently) static. We subscribe to a model-based approach to recognize storage operations. Technically speaking, we match background knowledge about storage processes against the observation to facilitate interpretation of the data. Since background knowledge is coarse and conceptual, the challenge is to mediate between the sensor-level and the conceptual level. Thus, the main challenge of employing a mobile robot observer is to develop a suitable knowledge representation of space and spatio-temporal processes.

4. Logistic Analysis and Optimization on Uncertain Information

In this section, we exemplify how logistic analysis and optimization is utilized in the given scenario. Figure 2 schematically shows the optimization loops resulting from the use of the mobile robot observer. The robot operates in a physical logistic system (in our example the warehouse). Operational decisions are made in a subsystem "operational planning and control systems". If at all and by which IT system these decisions are made or supported is not important for our approach. In a subsequent phase of in-process data acquisition the current warehouse state is detected without interfering with existing processes or systems. During its tour the robot detects the current state, resulting in multi-moment snapshots of the logistic system after many tours. On the one hand, these snapshots can be used to directly support operational processes, for example in a nominal/actual value comparison to check actual stock levels against expected stock levels (according to the warehouse management system).

Nevertheless, the true potential of our approach lies in further analysis of the multi-moment snapshots to, on the one hand, support a logistic process analysis and, on the other hand, detect patterns in them. Questions arising during process analysis can for example be: How is the material flow in the warehouse, which goods are handled and what values performance do measures like inventory turnover have for specific goods? Examples for patterns of interest include: "the track between storage racks A and B is always used as a one-way road", "product A is always stored near

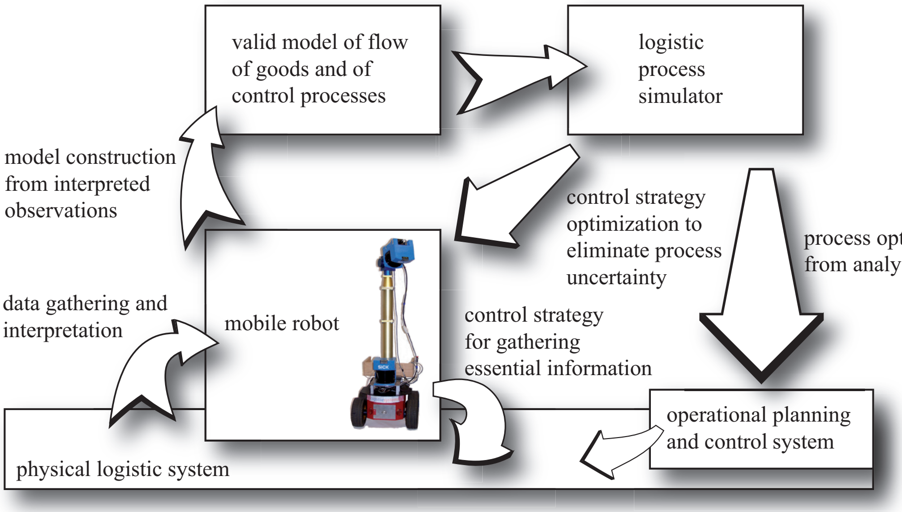

Figure 2: Optimization loop using the mobile robot observer.

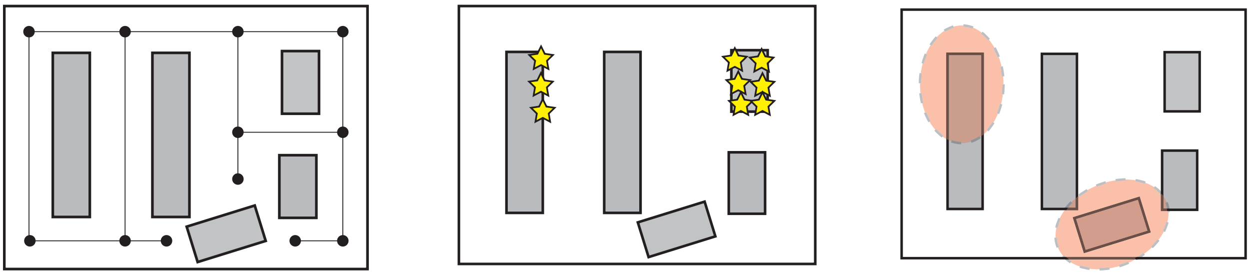

Figure 3: Representations of a schematized warehouse environment showing different aspects: Traversable paths (left), positions of objects (middle), and hot-spot regions (right).

the entrance". Such qualitative descriptions are directly readable from the spatial representations described in section 5. Areas in the warehouse changing frequently (so-called "hot-spots") can be identified as a further kind of pattern, and additional coverage processes can be invoked there.

The simulation of logistic systems with their complex processes and interdependencies is often the only practical tool to identify the most appropriate operational policy for storage and retrieval of goods. However, this requires a valid simulation model, reproducing reality with sufficient accuracy [8]. It appears unfeasible to derive such a model from the data of operational IT systems like warehouse management systems, but the knowledge acquired by a robot observer allows us to construct valid simulation models in a straight-forward manner.

A simulation model created this way can be the basis for various different optimization approaches, e.g., the selection of a proper storage policy as already mentioned before (which goods to assign to fixed storage spaces, which to store chaotically), or to perform a simulation-based layout optimization.

Once promising possibilities for optimizations have been found, they have to be implemented and tested in the real system. The robot turns out to be very useful for this task as well since the observation of the updated processes and structures can be used to evaluate whether the modified processes have been implemented correctly and the benefits of an optimization can be gained as expected.

5. Qualitative Representation of Uncertain Environments

Usual methods for goal-directed robot navigation are based on exact knowledge of the environment and detailed maps. Handling uncertain knowledge can be considered the most fundamental challenge for robot navigation, as all perceptions are naturally distorted, i.e., all information available to the robot must be regarded uncertain. In general, there are two approaches to tackle this problem [9]: first, by reconstruction of sensory data up to a detailed level using stochastic estimators, or second, by qualitative abstraction to an inherently secure, but coarse level.

In our scenario we encounter information at a high level of detail, but also on a high level of uncertainty, especially due to the underlying dynamics. The location of pallets and racks is variable, and stored goods are obstacles themselves and thus become part of the environment. Acquiring and maintaining a comprehensive and detailed map of the environment is likely to be infeasible. Yet, it is not necessary to record all information on a high degree of detail, it is rather important to focus on the *relevant* information. For example, the precise storage position of a frequently accessed good is irrelevant for recognizing that the good is stored in a too remote place. Thus, the main challenge is not to collect all the environmental data, but to *interpret* it appropriately.

Also, due to the dynamics of the domain we are operating in, data gathered in one snapshot must be expected not to be valid anymore at later point in time. To tackle this problem, we employ methods from spatial cognition that rely on the fact that humans are able to interact with their environment in an appropriate and efficient manner, even if they have imprecise and fragmentary knowledge about their environment only. Thus, concepts of human cognition are utilized for computational processes in time and space.

Instead of storing exact metrical data we represent information qualitatively on a higher level of abstraction using objects and the relations between them. The abstraction chosen has to be task-driven: On the one hand, any task requires knowledge on a certain level of granularity, and on the other hand, only a subset of the existing information is required to infer the needed behavior. We refer to subsets of information that become essential for a task at hand as *aspects*. For the given variety of tasks, representations on different granularities are needed that integrate different aspects of information. We call such representations *multi-aspect maps* [10].

Figure 3 schematically exemplifies different aspects for different tasks. The most important aspects for robot navigation tasks are the freely traversable paths within the warehouse, which are represented as graph structures representing connectivity of distinct places. For logistic optimization of the storage the travel distances between racks or pallets containing certain goods is the important aspect, represented by objects in space. Frequently changing areas in the warehouse (hot-spots) are represented based on regions; those have to be covered more frequently to reliably detect storage and retrieval operations. Robot navigation does not necessarily rely on an exact metric map that assumes a static world, but on paths and relations between object in space, that is, on the world's topological information (see [11], e.g.). Thus, the robot is able to exhibit robust and variable behavior based on general, uncertain information.

A characteristic of our scenario is that the kind of goods stored can be identified from their RFID tag. This classification provides semantics that is valuable information for process optimization, as, for example, route planning of forklifts. This enhances the path planning problem from shortest way calculation to a multi-parameter optimization problem.

The internal spatial representation of the robot serves as a semantic map: This enables for reasoning beyond geometrical knowledge. For example, a suddenly emerging obstacle consisting of milk cartons can be interpreted as a pallet stored there, and it can be assumed that it will disappear again after some time with a certain probability. Based on such assumptions it is also possible to reason about the storage area itself, e.g., about its degree of dynamics in certain areas or storage strategies of (human) stakeholders.

6. Conclusion and Outlook

This paper presents an ongoing project effort bringing together cognitive robotics and planning and control of manufacturing systems to develop an autonomous robotic observer of logistic systems and processes. Using warehouse logistics as an example, the paper presented the use of this robot for the optimization of logistic processes.

The combination of methods from spatial cognition with methods for process analysis and optimization of logistic systems gives rise to a new, minimally invasive approach for the in-process detection of system states, to derive optimization potential and to assess the practical effectiveness of these interventions.

Methods from spatial cognition allow an efficient handling of uncertain knowledge on a high level of abstraction. Data from the localization of RFID tags attached to goods or palettes can be linked with spatial information from the navigation data of the robot and result in an overall image of the logistic system's current state. Ongoing work addresses this data integration. Our mid-term goal is providing suitable processing of this data as a starting point for both logistic process analysis and optimization as well as for adaptation of the data acquisition strategy of the autonomous system.

Besides our current focus on warehouse processes we also want to investigate to which extent further data analysis is necessary and how to modify the approach to achieve the full potential of our system in different logistic usage scenarios in the long run.

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