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Leveraging passive monitoring applications in production and intralogistics

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Abstract

Today's rapidly evolving industrial landscape and the progressive digitization of products, processes, and resources require massive amounts of online data on the current production and logistical status. Fixed-positioned sensor systems have a constrained Field of View (FoV), while a mobile system can significantly extend these, enabling further applications due to the larger observed space. In this work, we elaborate on potential applications that utilize incidentally acquired data from various locations from the perspective of a mobile, vision-based sensor system. We exemplarily demonstrate an application within the scope of capturing and triggering the intralogistics chain with data from a vision-based sensor system that can be carried by an Autonomous Guided Vehicle (AGV).

Keywords: logistics monitoring; visual environment perception; mobile sensor system; incidental data acquisition

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1. Introduction

Comprehensive and detailed knowledge of processes and activities taking place in manufacturing facilities is an important building block for the management, control, error detection, and improvement of workflows. Process transparency allows for a clear understanding of the environment and ongoing activities and can help identify improvement areas [1]. A lack of transparency and inadequate information may lead to inefficient processes, huge communication efforts, and delayed detection of problems, deviations, and bottlenecks.

Particularly in large-structure, small-quantity production environments, such as aircraft production, it is not easy to record all processes in real-time. The complexity of simultaneously ongoing processes, the variety of manually performed work steps, and the large area to be covered are major challenges in achieving full transparency. Nevertheless, especially for intralogistics applications and demand-oriented, continuous material supply, knowledge about the position and status of logistic assets and information about completed and planned work steps are of great interest.

Monitoring the products, processes, and resources on the shopfloor can be achieved either by implementing fixed, singular sensor systems enabling specific applications or by building a mobile system with a set of sensors that moves across the shopfloor. Employing a mobile setup that does not actively travel but uses existing vehicles that can be retrofitted with such a solution, enables incidental data capture, allowing for various applications as the overall observed space is much larger than when employing fixed-positioned sensor systems. In this work, we target such a system, and our contributions are as follows:

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- We propose and discuss potential applications for passive monitoring in intralogistics and production based on incidentally acquired vision data.
- We showcase one specific application based on a prototypical mobile sensor system, the *SensorBox*. Further information on the technical setup of the *SensorBox* is given in concurrent work [16].

The remainder of this work is structured as follows: In Section 2, we present related works. In Section 3, we elaborate on the requirements for implementation and discuss relevant applications in more detail. In Section 4, we conduct an experimental study to showcase one application in a laboratory environment. We close with a conclusion and outlook in Section 5.

2. Related Works

The term 'logistics monitoring' is characterized in [2] as the foundation of logistics optimization and automation. The information available to control the flow of materials is key to increasing the efficiency of logistics processes. Localization technologies, e.g., using RFID tags or GPS, are commonly used for tracking and tracing in logistics. The use of RFID tags to identify individual parts in the automotive industry along the supply chain is proposed in [3], while [4] proposes tag-based tracking for further assets. Tags can also be used to track entire load carriers such as pallets or containers, but introducing tag-based technology into already established and operational large-scale logistics environments would require significant change to operation since one tag per object is required.

[5] surveys different logistic applications employing image processing for tracing, inspection, occupancy checks, object picking, and documentation. Others propose the use of stationary cameras in combination with 2D planar visual markers to identify and localize goods during the production process to increase transparency in worker decision-making [6]. Besides marker-based systems, more contemporary methods, like learnable deep neural networks, can also be used to detect and localize objects in a warehouse, e.g., pallets [7]. In general, the localization of logistics vehicles can either be achieved with self-localization, where cameras are mounted on the vehicle, or through target localization using static cameras in the environment [5].

[8] introduce a Cyber-Physical Production Monitoring Service System (CPPMSS), interweaving a business model with Cyber-Physical Systems (CPS). [9] discuss real-time localization technologies for production assets, [10] demonstrate a vision-based monitoring system for block assemblies in shipbuilding. The authors propose visually acquiring the assembly scene from above and comparing it with reference projections from the same perspective as the camera using as-designed CAD data to estimate assembly progress. The integration of vision-based activity detection and Business Process Models (BPM) in manual assembly tasks is proposed in [11]. The intersection of using Internet of Things (IoT) concepts and BPM and how the two areas can benefit from each other is described in [12]. The authors claim that IoT can extend BPM capabilities by providing real-time data to improve information flow, decision-making, and process optimization by enriching BPM with information from various sensors.

To our knowledge, the literature does not propose concepts for monitoring intralogistics and production sites through a non-invasive, passive, mobile system or applications, that we target in this work.

3. Passive Monitoring in Production and Intralogistics

A passive monitoring system aims to perceive its surroundings without explicitly moving the system to specific Regions of Interest (RoI). On the one hand, this allows for equipping existing, moving vehicles with the necessary sensors, which we describe as non-intrusive; on the other hand, we do not have to deal with explicitly stating RoIs. However, the downside is that an incidental data acquisition scheme does not ensure that all activities and actions are observed. Given that sensor solutions for a passive monitoring system must be non-tactile as well as non-invasive, vision-based systems, including 2D/2.5D/3D modalities, are most suited due to their inherent information richness and the view from the outside onto the objects of interest.

In the following sections we elaborate on the requirements of a mobile system for passive monitoring as well as applications. We then also further outline the concept of passive monitoring in intralogistics and production.

3.1. Requirements

Overall system requirements

A major requirement is that a mobile monitoring system must be able to detect its environment passively using only non-intrusive means. Additionally, the location where information is recorded must be captured, resulting in a localization and mapping component. Besides, to increase adaptability to different vehicles, it must also be able to function independently and should be battery-operated.

Sensor and processing requirements

Cameras providing 2D images produce information-rich and dense data, which can be further processed to gain and extract desired information. Moreover, multiple cameras in a fixed rig provide a more holistic Field of View (FoV) than a single camera. A slight downward tilt is required since the application focus is on the perception of objects in delivery areas and paths. In addition, a slight overlap of the cameras is required to achieve a common FoV between the cameras, to minimize the dead zone, and to allow extrinsic calibration. Color images and depth information together allow subsequent detection of objects in 2D or 3D. Since 2D data is not directly distance-aware from one point of view, a LiDAR is more suited for fast and accurate localization and mapping than a set of 2D/2.5D cameras. Furthermore, an integrated processing unit is necessary for online processing and evaluation and for writing the data to a disk for offline analysis tasks.

Geometric requirements

In the context of passive observation and equipping existing logistic vehicles, the use of Autonomous Guided Vehicles (AGV) as carrier platforms is a viable option. During the course of the day, these vehicles move through various areas of the warehouse and actual production site and can collect data passively as they pass by. Considering an AGV for transport, these vehicles often transport goods using standardized load carriers, often termed KLT. Therefore, an integrated sensor system can, e.g., be perfectly fitted into such a KLT box, which is standardized in VDA4500. A major advantage of such a KLT-integrated system is that it can be part of other handling activities since the outer dimensions and handling interfaces are standardized. Moreover, as an integrated and self-sufficient mobile system, it can easily be switched between carriers and be parked, e.g., in standard shelving systems. Nevertheless, other concepts for direct mounting of sensors and processing units onto carrier vehicles are also possible.

3.2. Applications

The outlined mobile sensor system can be used for a variety of applications, which we divide into four different categories:

- **Capturing and triggering the intralogistics chain:** The vision-based recognition of material carriers (e.g., small load carriers, material trolleys, or material-specific jigs) and more extensive goods without dedicated means of transport allows for early material availability checks and demand-oriented planning of subsequent work steps. Such checks can then serve as the basis for triggering further material orders, requesting subsequent deliveries of missing supplies, or adjusting an assembly procedure according to current material availability.

  Vision-based solutions demand robust, learnable methods that often require synthetic training data in the scope of unique objects [17]. However, pre-trained models are publicly available for recognizing common objects like pallets, box-styled packages, or other vehicles such as forklifts and lift trucks. The use case, therefore, defines the complexity and engineering effort to enable such an application. Meanwhile, platforms emerged that can simulate the intralogistics domain for generating synthetic data that subsequently serve to close the simulation-to-real gap more and more; an example is Nvidia Isaac Sim [20].
- **Assembly progress detection:** Continuous monitoring of the current assembly status allows the comparison of the actual status with the target status, as proposed in [10]. This information enables documentation and reaction if deviations or anomalies from the planned process occur. This is particularly relevant for fixed position assembly, e.g., as in the case of an aircraft final assembly line. The product remains at a station for a more extended period of time, and not all assembly steps are always recorded in real-time during this period. Additionally, process correctness checks could be executed from different perspectives and orientations, which then can subsequently be used for quality documentation. In the scope of incidental data acquisition, sensors with a large FoV and wide range are to be prefered to detect changes, e.g., a top-mounted LiDAR sensor that can monitor a large area. On the other hand, dense 2D images can give a more in-detail view, thus a combination will be beneficial. For such an application, the use case defines the required sensor modalities. In the scope of aircraft assembly, perceiving the current position of a to-be-mounted large-scale component, e.g., a tail wing, fits this category and can, for example, be monitored through a combination of LiDAR and 2D images.
- **Anomaly detection and obstructions:** The presence of objects and vehicles as well as currently ongoing processes can also be compared with the typical environment and evaluated for deviations. Detecting anomalies and deviations can be of great interest for quality assurance and process optimization. Anomalies and obstructions include, e.g., waste and components on the ground that should not be there, or obstacles and blockages caused by improperly parked transport trolleys that might interrupt the workflow. To enable image processing applications for such an application, anomaly detection methods can be used, e.g., using models that are able to recognize deviations from a learned normal state. For such models domain-specific training data is necessary. An alternative is to use methods for change detection, e.g., the comparison of the environment in 2D or 3D between defined time frames. A change detection application is particularly cost-effective if a class-agnostic method provides sufficient information straight away while a restricted set of objects is selected for training a model, inferring more in-depth semantic information.
- **Data mining:** We summarize the last class of applications as data mining, targeting the extraction of information from a large, diverse, and often unstructured set of data. The continuous collection and accumulation of data from various locations in logistics and production allows to employ standard tools for data and process mining.

  An important objective when deciding which data to collect is often not directly linked to a specific use case; instead, gathering cost-effective and non-laborious data is of interest. Information that can be derived from vision-based systems can, e.g., provide insights about human movement areas and paths, delivery times, number of stops or idle-times. In general, data mining can help to get a profound understanding of ongoing processes, possible trends and changes, serving as a basis for long-term improvements. In the scope of aircraft manufacturing and assembly, [18] gives examples of data mining and details individual challenges and potentials.

Merging the information obtained from the different applications and locations demands a control layer tool such as process models for the given environment, which processes the individual information, providing transparency and allowing for more detailed documentation and traceability of processes currently taking place. An exemplary, simplified process model for a material availability application is given in Figure 1. Considering a specific material storage area ‘A’, its occupation status ‘S’ can be modeled. To trigger transitions, a material availability application, as discussed above, can serve for monitoring. We further elaborate on it in an experimental study in the following section.

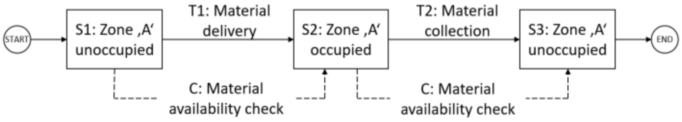

Figure 1: Simplified process model for modelling the material availability in zone ‘A’. States are represented with an ‘S’, transitions with ‘T’, the material availability check data flow with a ‘C’.

4. Experimental Study

In the following, we demonstrate an example of an application from the category “Capturing and triggering the intralogistics chain” as outlined in Section 3.2. We use a prototype built according to the derived requirements for a mobile, multimodal sensor system. The application is embedded in the process model according to Figure 1. We start by outlining the specific sensor system prototype (*SensorBox*), then describe the study design and discuss our test runs. Further technical information on the *SensorBox* is given in concurrent work [16].

4.1. Prototype

As we aim to use an AGV as our means of transport for the data acquisition we built a prototype we call *SensorBox*. It fits into a 600x400x220mm standard load carrier according to VDA4500, as described in Section 3.1. The box’s front is cut open to allow for a clear view. Multiple cameras are mounted on an internal frame in a way that prevents them from protruding from the side or front of the box. Three industrial cameras of type IDS uEye UI-5280-CP-C-HQ equipped with lenses with a focal length of 8mm and an aperture angle of 58.5°×45.3° are mounted in the upper front and have a slight downward tilt to capture the near field and the floor. Their total FoV in a horizontal direction is about 153°, which allows them to capture objects lateral to the box when passing by. In addition, two Microsoft Azure Kinect cameras capture the near field and provide depth data as extra information. A SICK MRS1104C LiDAR is mounted on supports and will be used for navigation and referencing. Data processing takes place on an Intel NUC11PH with Nvidia RTX2060. There is also space left for a battery in the rear area for self-sufficient operation. We use the ROS [13] software framework, which allows for simple integration of the various sensors in a modular way. For navigation and orientation in the environment, we use KissICP [14] to obtain a map and the moved trajectory. As we plan to use the system in an actual production environment, special attention is paid to privacy protection. After recording, the raw data is processed with a YOLOv8 network [15], during which the image data is examined for humans. These are immediately masked, setting pixel values to 0, or can be blurred using median blur. A more detailed explanation of the software structure and algorithms is presented in [16]. Figure 2 depicts a simplified rendering and the FoVs of the sensors, respectively.

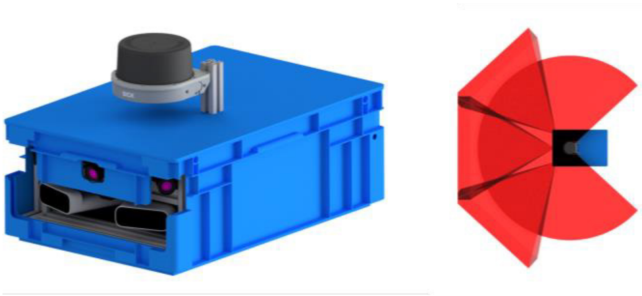

Figure 2: Renderings of the final *SensorBox* concept. Left: Front view. Right: Top view with visualized RGB cameras’ and LiDAR scanner’s FoV.

We used our prototype for initial tests in our laboratory environment. The test runs were carried out by manually pushing a hand trolley to simulate an AGV.

4.2. Study Design

In our study, we want to demonstrate a material availability check of a specific area in our lab space, depicted in Figure 3. There is a corridor in the middle, with stations and lab setups on either side. We assume the corridor to be the transport route of our AGV with the *SensorBox* as its payload. Three material storage areas (‘A’, ‘B’, and ‘C’) are marked with adhesive tape and ArUco markers at their corners to enable robust detection. In our test scenario, we conducted two exploration trips. The area ‘A’ in the lower left in Figure 3 is to be checked for material availability to use that information for updating the process model given in Figure 1. We use a pallet as an exemplary material item. Nevertheless, one could also look for use case-specific materials such as KLT boxes, wire lattice carts, or specialized jigs.

The material availability check is composed of the following:

- We implement **material detection** using a standard YOLOv8 Nano [15] on the RGB images. The YOLOv8 architecture combines the two required tasks, classification and localization, and allows for high frame rates and online operation. For our application, we used a pre-trained YOLOv8 and fine-tuned it, training 50 epochs with all but the last layer frozen using a publicly available pallet dataset [19].

- **Material storage area detection:** To detect both occupied and unoccupied material storage areas in the surrounding, we use ArUco marker detection and project a rectangular bounding box delineating the area on the floor. We can derive information about material availability by combining the results from material detection and the current t AGV location.

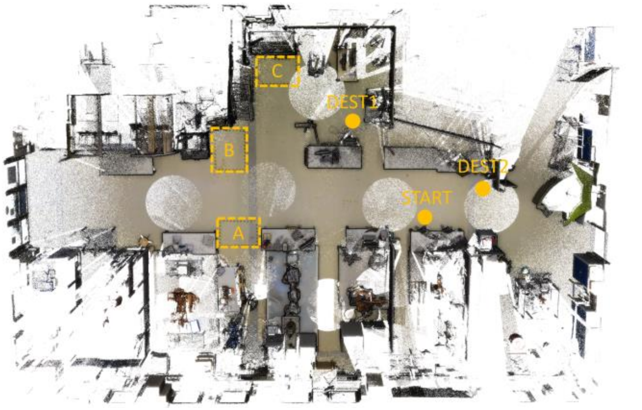

Figure 3: The lab space for test scenarios recorded using a Leica BLK360G2 laser scanner. Material storage areas are bordered and marked with letters ‘A’, ‘B’ and ‘C’. Start and destination points for the test runs are also marked and labeled.

4.3. Test Runs

The route begins at the ‘START’ point indicated in Figure 3. The first run then goes toward zone ‘A’ and continues to ‘DEST1’. The second run starts at the same position, passes nearby zone ‘A’, and ends at ‘DEST2’. During the test runs, a LiDAR-based map was generated by KissICP that can be aligned with the reference map of the lab space.

First run: Shortly after beginning the journey, when reaching waypoint ‘W1’, a pallet was detected in the left camera image (s. Figure 4). The current position of the *SensorBox* at waypoint ‘W1’ is displayed in Figure 5. In conjunction with the current position and orientation and taking the ArUco marker numbers into consideration, the information was used as input for the process model in Figure 1. It triggered the transition ‘T1’ from state ‘S1’ to state ‘S2’, thus confirming that a worker has delivered the pallet.

Second run: Before starting the second exploration run, the pallet was removed to simulate process progress from state ‘S2’ to ‘S3’. The result obtained from the material availability check when passing nearby waypoint ‘W1’ from the first test run is visualized in Figure 4. As can be seen, no pallet is detected, and the floor region that corresponds to the material storage area is highlighted based on the detected ArUco markers. This information triggered another transition to state ‘S3’ in the process model.

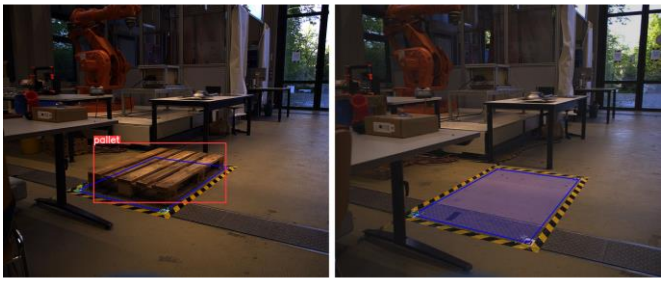

Figure 4: Camera image of zone ‘A’. Left: Identified pallet and projected edges of the area using ArUco markers (green) at the corners during the first test run. Right: An empty zone percevied during the second run when positioned near waypoint ‘W1’.

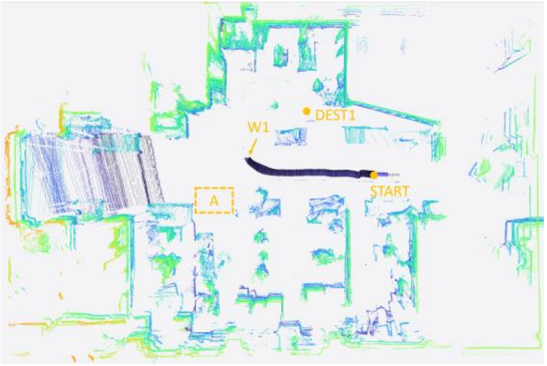

Figure 5: Projection of current *SensorBox* position on the final map when reaching waypoint ‘W1’ during the first test run. Annotated are also the start and destination as well as the material area of interest.

5. Conclusion and Outlook

5.1. Summary

Profound knowledge of current processes and activities is of great importance for reliable and efficient production. Especially in intralogistics, smooth workflows, and punctual material deliveries are essential. In order to meet the requirements of logistics processes in today’s rapidly evolving industrial landscape, large amounts of real-time data are required to enable a flexible and demand-oriented material supply. If retrofitting a production environment with stationary sensor technology is not desirable, the use of a mobile, flexible monitoring system can represent a potential solution and is a promising addition to existing technology.

In this work, we presented a variety of possible applications for a mobile sensor system to monitor products, processes, and resources in production and intralogistics. We further presented the implementation of a specific application using data from a prototype called *SensorBox*, which can be used in conjunction with existing intralogistics transporters. Due to its passive nature, it does not interfere with existing working procedures and can be used during off-times and idle periods to gather information and shed light on previously unknown activities. Such data can then enrich process models, serve as action triggers, enable us to recognize delivery deviations and production anomalies, or detect obstructions. Additionally, it can collect large amounts of data to enable further analysis and integration into superimposed systems such as a Warehouse Management System (WMS) or Manufacturing Execution System (MES).

5.2. Future Work

In the future, we plan to expand the application from the experimental study for material availability checks and include other objects. Furthermore, we want to also implement anomaly detection and assembly progress detection. Besides, we plan to test the prototypical system using an AGV at a production site and consider equipping other vehicles, such as forklift trucks or tugger trains.

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