Monitoring production and logistics processes with the help of industrial image processing

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ABSTRACT
With the increasing prevalence of industrial image processing (IIP) in business processes in general and in logistics and transport operations in particular, several application areas and business functions could be identified as suitable for camera-based monitoring tasks. The present paper presents an insight into IIP applications in production and logistics.

Keywords: Production, Logistics, Industrial Image Processing, Machine Learning, Process, Monitoring

INTRODUCTION

Travel distances and time spans of globally manufactured products to reach their final destinations is ever increasing, leading to a wide variety of goods available at one's daily disposal. In fact, it is the result of big efforts and effective teamwork in which logistics plays a very important role by planning, organizing, coordinating and controlling the flow of goods along local and global supply chains.

The main directions of logistics in the different stages of the supply chain are categorized according to the traditional course of processes, ranging from the procurement of the material to be processed over the provisioning of materials at the production line up to the delivery of the finished product to the customer as well as accompanying aspects of planning and information.

A major prerequisite for smooth logistics operations is the availability of the right information at the right time and in the right format. With such information, processes can be monitored and controlled effectively. Many technical systems aim at providing such information in order to improve effectiveness and efficiency of logistics processes (Alias et al. 2014a). However, operational reality looks quite different as useful information is scarce, difficult to obtain or to identify or little trustworthy. Unavailability, unreliability and bad profitability are the three possible situations that can be distinguished referring to the availability of information about process operations and their respective status (Alias et al. 2014b).

A large-scale adoption of a multitude of sensors and actuators for the sake of providing measurement information about one or few particular subjects is yet to follow in many companies (Dimitriou 2011; Skoogh and Johansson 2008). The three above-mentioned reasons play a role when it comes to the slow take-up of the growing number of sensors and actuators on the market. The problem of lacking transparency in process operations is not necessarily tackled by the devices as partial or complete unavailability of information, unreliability of measurements and bad profitability of the installation still may exist despite the introduction of the new devices.

A minimal time difference between noticing a deviation and organizing remedy is often preferable (Hackathorn 2004). For an immediate reaction on an operational level and for reviews of performance for tactical modification, capturing real-time data about the vehicles and the related processes is inevitable. Data collection, however, cannot always rely on traditional concepts and requires new technical approaches in order to generate new (and better) information about the surveillance areas.

An innovative, reliable, cost-efficient and effective means to capture information about the actual process status and to monitor operations is the use of cameras. Cameras provide a visual representation of a system and the process therein, facilitating retrospective analyses of situations and continuous monitoring of processes – either manually or semi-automatically. In addition, cameras help to overcome three above-mentioned weaknesses of today's approaches towards real-time monitoring systems as unavailability and unreliability of information as well as bad profitability of solutions are addressed explicitly. Earlier research comparing camera-based solutions with sensor-based approaches towards collecting data about certain aspects of logistics processes supports this assumption (Alias et al. 2015; Özgür et al. 2015).

PROBLEM DEFINITION

By the growing use of cameras in company premises, the adoption of industrial image processing as an essential part of operative monitoring systems is ongoing. Cameras and camera-based monitoring of processes promise an additional pool of information about ongoing processes and their respective statuses.

Logistics is a major function in the value creation process along a supply chain. The transportation and logistics domain, considered as one of the largest business sectors in the world and accounting for up to 20% of a country's Gross Domestic Product, is an ideal environment for new types of solutions promising an increase in the efficiency of the activities and, thus, an improvement of the competitiveness of a company. Hence, it is a perfect field for applying industrial image processing in an industrial manner for monitoring and managing the respective processes.

With the increasing prevalence of industrial image processing in business processes in general and in logistics and transport operations in particular, several application areas and business functions could be identified as suitable for camera-based monitoring tasks (Alias et al. 2014b).

Previous research has shown that cameras and industrial image processing algorithms are capable of helping to realize a total of ten monitoring functions, ranging from sheer detection of objects to the sophisticated control based on camera-based impulses (Alias et al. 2014b). Therefore, they can act as an effective process control in a logistics environment. Figure 1 shows an overview of the ten major camera-based monitoring functions and possible examples from the transportation and logistics sector. Those functions are capable of covering a vast majority of information required for monitoring and controlling actual processes in logistics.

Referring to the earlier mentioned problems regarding the availability of information about process operations, cameras promise to be an effective countermeasure to all three problems (Alias et al. 2014b). The unavailability of real-time information of the actual process status can be tackled with the solution as the captured information is more effective than ordinary sensors and easily integrable into the existing systems landscape.

	Examples from the T&L sector		
Detecting	consignments / pallets	forklifts	boxes
Counting	consignments / pallets	system entries/exits	vehicle hauls
Identying	forklifts	boxes	entrance gates
Measuring	process times	speed	distance
Examining	conveyed goods (e.g. boxes or objects)	coated goods	boxes
Locating	consignments / pallets (in warehouses)	objects (in production line)	forklifts (in warehouses)
Tracking & Tracing	consignments / pallets (in warehouses)	objects (in production line)	forklifts (in warehouses)
Navigating	consignments / pallets (in warehouses)	objects (in production line)	forklifts (in warehouses)
Alerting	temporal deviation (e.g. process times)	spatial deviation (e.g. location)	quality deviation (e.g. spraying process)
Controlling	generation of orders (for forklift hauls)	setting of (conveyor belt) switches	control of gates (for entry to areas)

Figure 1 – Examples of camera-based monitoring functions in the transportation and logistics sector (Alias et al. 2014b)

Without being directly installed on a facility or involved in a process, the unreliability of the collected information is overcome as process control opportunities are higher with the help of camera-based monitoring. The susceptibility to manipulation, wear and tear and defects is lower for cameras than for sensors. However, there are other disturbing influences on cameras that need special attention, such as bad recognition due to reflection, dust, or glory. With a low setup effort and existing industrial image processing algorithms in combination with an adequate engineering effort allow a good cost-benefit-ratio, solutions based on simple off-the-shelf cameras help to avoid expensive solutions and to increase the attractiveness for small and medium-sized enterprises.

As has been shown in earlier research, the general applicability of cameras and industrial image processing has already been proven for a series of environments. Earlier publications refer to various application examples, such as monitoring storage areas, counting objects entering and leaving the field of view of the camera, locating logistics objects in a surveillance area, tracking the path of transport boxes in a conveyor system, and monitoring the occupancy status of the load handling units of industrial trucks (Alias et al. 2014b; Özgür et al. 2015). However, these results refer to experiments conducted in an artificial setting rather than under realistic conditions. In the present paper, the applicability of camera-based monitoring functions in an industrial environment is introduced based on use case examples of actual logistics and production processes of German enterprises.

RELATED WORK

With respect to camera (and sensor) applications in intra-logistics, a whole string of projects and applications can be found. An analysis of such projects has already been published earlier (Alias et al. 2015), of which an excerpt is presented here again.

Schuldt and Gottfried have adopted camera sensors for supervising the environment of the vehicle as part of the technical components in order to introduce new approaches to automatic navigation of autonomous vehicles, e.g. automated guided vehicle systems, in intra-logistics (Schuldt and Gottfried 2008). In another German research initiative, information about logistics processes on warehousing premises is collected by combining different sensor information about various statuses of industrial trucks and consignments (Borstell et al. 2014). With the help of cameras mounted on the ceiling, matrix code markers on the forklift and software which analyzes the recorded images and videos, the vehicles can be located in the field of view of the cameras (Borstell et al. 2013). Yet another German research initiative addresses the need of status information by using a camera and industrial image processing techniques (Hohenstein et al. 2012b). The high flexibility of cameras helps to deal with unforeseen adaptation needs when it comes to reliable detection of object conditions. Therefore, the researchers have opted for the camera as their solution technology, esp. replacing ultrasonic or laser sensors and radio location or inductive RFID tracks (Hohenstein et al. 2012a; Jung et al. 2014).

SOLUTION CONCEPT

As already presented before, the camera-based solution approach can be subdivided into four major elements: the cameras, the industrial image processing algorithms, a machine learning (ML) library and a library for Augmented Reality (AR) fiducial markers (Alias et al. 2014b; Özgür et al. 2015).

As to cameras, simple and cost-efficient network cameras have been mounted on the ceiling of the warehouse. The intelligence lies in the application and adoption of suitable industrial image processing algorithms rather than sophisticated hardware devices. From a financial point of view, the use of existing image processing algorithms, esp. from existing open source image processing libraries, such as Open CV, which is the most popular open source computer vision library and features the largest programmer community, for the video analysis of a recorded process leads to an increased attractiveness of the solution (Özgür et al. 2015). Speaking of cameras, certain preconditions need to be considered if reliable data is to be collected from video streams by means of industrial image processing algorithms (Spinnler 2012).

With respect to image processing algorithms, there exists a bunch of appropriate methods for the diverse application opportunities in the field of transport and logistics. In principle, the detection and tracking of objects in video streams is carried out with the help of four characteristics, i.e. color, edges, motion, and texture (Yilmaz et al. 2006). Consequently, the different methods for detecting and tracking objects center these four characteristics (Alias et al. 2014b).

The ML library, Dlib-ml, is an open source library for both engineers and research scientists, which aims to provide a similarly rich environment for developing machine learning software based on C++ language, has been used (King 2009). Offering faster training, the same detection rate and significantly lower false positives than OpenCV, Dlib supports importing and exporting to OpenCV image representation. In the experimentation environment, the processing has taken place using Dlib training algorithm based on structural support vector machine. Beginning with video recording and conversion into individual frames over frame selection for the training set and labelling the objects of interest in the training set up to training the machine learning algorithm and applying it in the video stream belong to the course of action (Özgür et al. 2015).

In preceding research, using markers for identification of objects has turned out to be far more effective than relying on object-specific characteristics only. The major advantage of using markers is the capability of being able to detect an object unambiguously and to avoid erroneous or absent detection. With respect to the AR fiducial markers, ArUco matrix codes have been used for detecting and tracking the forklifts. ArUco is a minimal library for Augmented Reality applications based exclusively for OpenCV (Garrido-Jurado et al. 2014). The reason for choosing ArUco lies in its reliability in detecting so-called high reliability markers (HRM) even for smaller sizes, which has posed a practical problem in many cases of the past. A major asset of the ArUco library is that the position and the orientation of the marker can be detected, allowing to derive the position and orientation of the forklift from it (Özgür et al. 2015).

The video is recorded by network cameras and saved on a local server on which the captured video streams are examined by means of the above-mentioned algorithms (Alias et al. 2014b). By analyzing the video stream with the help of industrial image processing algorithms, the data derived from the observed process is captured and written into log files. The log files may take shape in different kinds, depending on the configuration. One approach writes the time stamp, the marker ID, the position coordinates and the load status information line by line for a defined time interval, for example, every second, every ten milliseconds, or every fifth frame. For the calculation and derivation of necessary information about the recorded process or the observed facility and for the further use of the captured data, these log files then need to be processed and pre-analyzed. Such a generic and configurable format safeguards a broad compatibility with back-end systems receiving and using the data written in the log files (Alias et al. 2014b).

With respect to logistics processes, industrial trucks like forklifts are considered as key performance enablers in logistics processes. Monitoring their activities allows deep insight and understanding of the processes they are used for. Hence, the decision-makers strongly focus on the optimal utilization and the prevention of waste in relation to the use of forklifts. Accordingly, the objects of interest in the experiments conducted in industrial environments were the industrial trucks. Both information about the position and trajectory of the forklifts and the status information of the occupancy of the fork over time were collected. By knowing both pieces of information, the activity profile of the vehicle can be derived and, relatedly, the underlying processes understood. Despite being used as a means for transportation, the main activities and the most interesting information are the load status changes. As soon as the load status is matched with the position of the vehicle, it is possible to recognize whether an ordinary storage and retrieval has taken place or whether an extraordinary incident has taken place. By capturing the information with simple and cost-efficient cameras supports the vision of enabling effective process monitoring and control based on a rich information base at reasonable effort and low cost.

In the following, the present paper presents two use case examples. One application example refers to production logistics, in which finished and semi-finished goods are carried to and from the production facilities to buffer and storage areas. Another application example presents the applicability of camera-based monitoring systems for tracking storage of consignments (as part of the goods receipt process) and their retrieval (for the outbound process) in a warehouse.

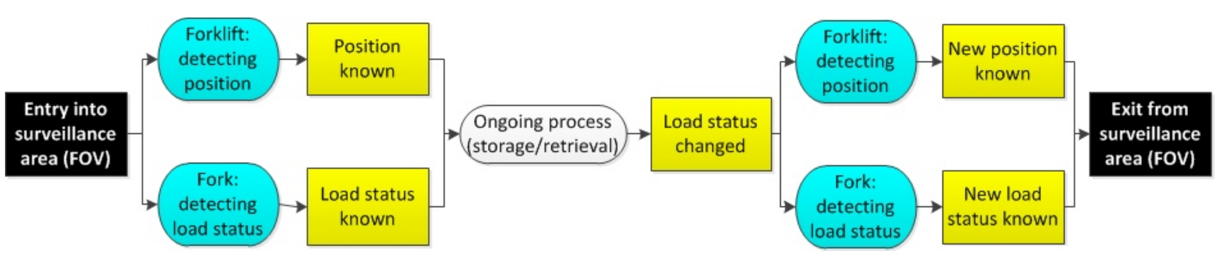


Figure 2 – General course of action of camera-based monitoring in the production and logistics use cases

In principal, both use cases follow a similar course of action which is illustrated in Figure 2. The industrial truck, equipped with an ArUco matrix code, enters the surveillance area which is covered by one or more cameras. On entering the field of view of the camera, the position of the marker is detected. In addition, the fork occupancy level of the forklift is captured. As part of the storage or retrieval process, the forklift collects a consignment from a certain spot or delivers a good to a certain place. In that very moment, the status change of the fork and the position of the vehicle are detected and written into the log file. The latter exhibits all position and load status changes over time and allows a detailed understanding of the activity profile of each vehicle tracked. By means of the log file, the actual processes may be mapped in the back-end system so that the current status on the shop-floor is also represented in the pertaining information system which again enables decision-makers to act and react without latency. The detection of load status changes can be repeated in case of the vehicle performing double cycles or several single cycles within the surveillance areas. Once the operation has been finished, the vehicle exits the surveillance area and the monitoring of the processing terminates because the vehicle is not visible or detectable anymore.

With respect to recognizing the forklift by means of the ArUco matrix code and detecting its load status, two alternative approaches can be pursued. In the first approach, both pieces of information are collected separately. The detection of the ArUco matrix code is not linked to the detection of empty or laden forks. The same video stream is used for both algorithms, i.e. both for locating the code and detecting the load status. In the log file, both threads of information then need to be consolidated in order to get the entire picture about a process. In the second approach, the recognized matrix code is the starting point for the definition of a region of interest in the video stream and its frames. The ArUco matrix code is mounted on top of the forklift so that the cameras at the ceiling have an uninhibited view of them. From above, the load handling units of the vehicle are clearly visible as they are located in front of the marker. Thus, the area in front of the matrix code is defined as the region of interest so that the load status of each forklift can be determined by focusing on the region of interest. While in the first approach, it is theoretically possible to obtain information about the position and the load status of a forklift separately, the second one does not allow it since the detection of the load status depends on the recognition of the matrix code. However, the performance of both approaches varies from one another despite a detection rate of the matrix codes nearly hundred per cent. As has been shown in earlier research, detecting the fork with cameras is possible but exhibits some weaknesses and unreliability (Özgür et al. 2015). By linking the fork detection area to the detection of the matrix code, the search space for the sought theme, i.e. the empty or laden fork, is narrowed. On the contrary, detecting the fork with the camera only suffers from effects of occlusion due to the vehicle moving to the edge of a camera's field of view and, thus, inhibiting the view at its load handling unit. Moreover, marking the fork with a characteristic feature has turned out to help considerable in order to raise the detection rate of the fork (Özgür et al. 2015).

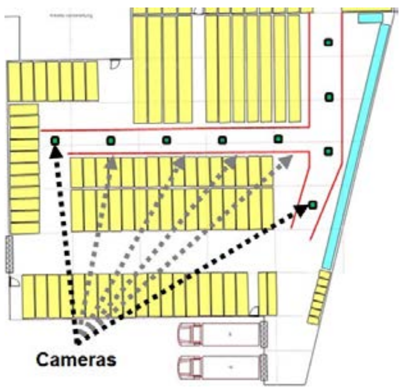
USE CASES

Use Case Logistics – Managing warehouses

For the logistics use case, the central warehouse of a German distributor of electronic goods has been selected as test site. Situated in the West of Germany and near to the German-Dutch border, the company imports large white goods articles from Eastern Asia and distributes them to retail stores and electric retailers in Germany and Central Europe. With approximately 12,000 40 ft. containers arriving at the company premises every day and 30 million units being sold annually, a lot of forklift handling for the purposes of storing entering goods and retrieving exiting articles, respectively, need to be realized in the central warehouse. To be able to do so, the company employs nearly 30 forklifts and clamp forklifts, for the handling activities.

The goal of the logistics use case was to prove the feasibility to run a warehouse management system for block storage warehouses with the help of camera-based data. In order to attain that goal, the forklift movements with empty or laden forks need to be monitored and the load status changes within the surveillance area carefully logged.

For testing purposes, a surveillance area has been defined; encompassing nine cameras and approx. 30 storage places (see Figure 3). The consignments are received and recorded in the company systems at the entrance gates from where they are stored in the various storage places. As a distributor of occasionally large white goods, the organization has defined rough zones in which area certain types of goods are to be stored. So, the precise location of each consignment is not as important as the position of a type of product within the entire warehouse space. The collected data is written into log files and later used in the warehouse management system w3/max of w3logistics AG, a German provider of WMS solutions.



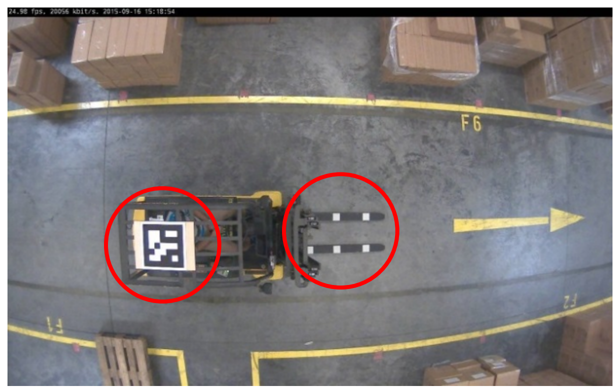


Figure 3 (left) – Layout of the test area and positions of the cameras therein

Figure 4 (right) – Forklift with ArUco matrix code on its top and a color pattern on the fork (Özgür et al. 2015)

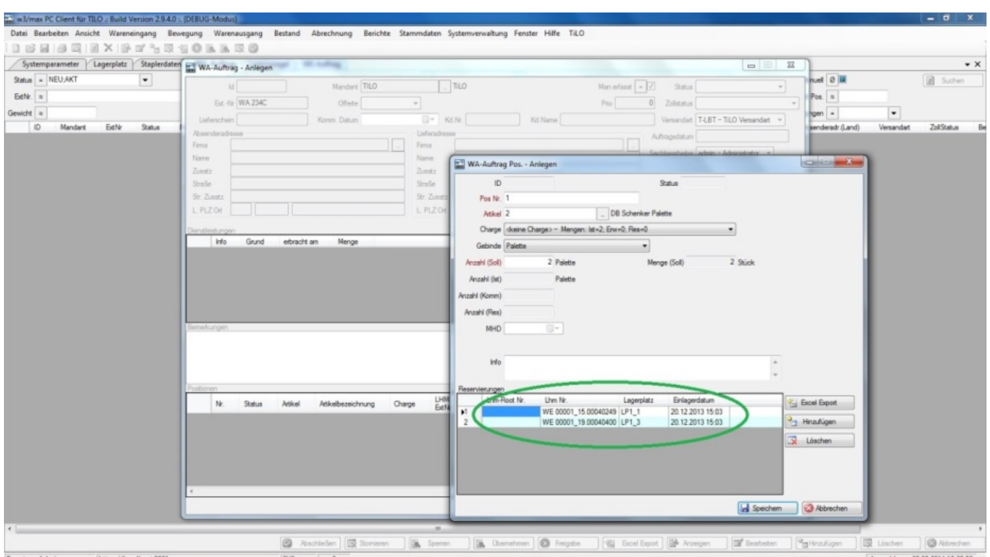


Figure 5 – Screenshot of an update entry in the warehouse management system

The cameras need to recognize the position of the vehicle by means of the matrix code on its top and to detect the load status of the forklifts. Figure 4 shows the forklift equipped with the necessary auxiliary means. The position information in the video frame of each camera is linked with coordinates in the real warehouse so that the different storage places and their counterparts in the respective video frames are known to the system. The load status information is collected independently from the matrix code on top of the forklift. So, any load status change in the video stream can be translated into a storage or retrieval operation in the warehouse. With the both pieces of information over time written into log files, the warehouse management system may retrieve those files in order to update its own inventory level for each storage place.

Figure 5 shows such an update entry in the warehouse management based on the information captured by the cameras. The tests have shown the general applicability of camera-based monitoring in order to manage entire warehouses and to keep track of the inventory levels therein.

Use Case Production – Controlling buffer and storage areas

The production use case has been examined at the premises of a German producer of plastic tubes and pipes. With a highly customer-oriented attitude and a product range of almost a thousand different products in many different colors, out of various materials and to be used for most diverse purposes and application areas, the company has to ensure a high degree of flexibility in its production planning and operation. After the various steps during the production of the tubes and pipes, the semi-finished pipes need to be rolled up on a drum and transported to buffer storage areas before being retrieved for the subsequent production step. After the final transportation, the finished items need to be stored in the finished goods warehouse. The numerous transportation tasks are realized with a heterogeneous fleet, mainly consisting of large-size forklifts and special hand pallet trucks.

The goal of the production use case was to detect empty and laden transports between the production area and the buffer storage area. By identifying the forklift and recognizing its load status, the movements between the production area and buffer storage can be recorded in an automated manner, esp. when the information from the respective production lines, e.g. about the recently finished products or the ones to be produced next, are combined with the storage and retrieval information.

For testing purposes, two major areas have been selected for surveillance. The first one is the entrance and exit gate of one production hall whereas the second one is the entrance to the consolidated warehouse for finished and semi-finished goods. For instance, by detecting the pick-up of a drum at the production hall by a formerly empty forklift and the delivery to the storage area for semi-finished products with the help of cameras and industrial image processing algorithms, the decision-makers are provided with real-time information about the actual progress on the shop floor.

The cameras are supposed to detect the vehicle and its position by means of the matrix code and to perceive the load status of the forklift. Figure 6 shows the forklift equipped with the ArUco matrix code on its top, carrying an empty drum. By detecting a forklift in the respective field of view of either of the cameras, the real position of the vehicle is known to the system and the decision-makers. With the help of camera-based detection of load status changes, it can be understood whether the vehicle has started or completed a storage or retrieval process. Moreover, the system – in its ultimate configuration – allows the differentiation between empty hauls, hauls with an empty drum and hauls with a finished or semi-finished product on the fork.

Figure 6 – Forklift with ArUco matrix code on its top and an empty drum on the fork

The collected information are written into a log file but can also be used in connected systems for subsequent use. In the experiments conducted, this was not in the focus of the research though. Similar test have also been run with alternative companies in other industries, yielding comparable results. The demand for camera-based information about buffer storage areas is high as standardized solutions are rare on the market and reliable information, thus, virtually not available.

CONCLUSION

Monitoring and controlling logistics processes requires much more shop floor information which is hardly available. Required information is not available, not reliable or not economically obtainable. Apart from the increasing prevalence of all types of sensors, cameras gain growing significance by promising a cure to that problem. Cameras have already proven to be capable of realizing ten different monitoring functions as they have been successfully experimented within earlier research endeavors.

In the current paper, the focus lies on the applicability in industrial environments, i.e. on use case examples of actual logistics and production processes. The use cases have shown the effectiveness of gaining process information and, thereby, a means to monitor and control operations with the help of camera-based monitoring.

OUTLOOK

Both the accuracy of forklift positions and the status detection of the load handling units require further improvement, esp. in view of accuracy and reliability. Hence, future research will focus on improving the machine learning algorithms and, thereby, the results of detecting the forklift position and the fork load status. By this, teaching the camera-based monitoring system with the help of the sensor-based fork occupancy detection helps to improve its accuracy and reliability rates. Moreover, the comparison of camera-based solutions with sensor-focused approaches needs to be elaborated more upon. Another future field of activity is the deeper integration of camera-based information into the existing systems landscapes.

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