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ORIGINAL PAPER

Marker-based tracking in support of RFID controlled material flow systems

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Abstract In this study, we present a novel approach for continuous detection, localization, and identification of parcels and bins in automated facility logistics systems. It presents a distinct departure from the traditional system design: light barriers and barcode readers are substituted by low-cost cameras and few RFID readers. By combining vision-based systems and RFID systems, this approach can compensate for the drawbacks of each respective system. For example, only the vision system is used for localization. The main part of our paper describes computer-graphics methods specific to the given problem to both track and read visual markers attached to parcels or bins. In addition, we use information from the RFID system to narrow the decision space for detection and identification. From an economic point of view, this approach can lower the costs of changing a material flow system.

Keywords RFID · Computer Vision · Tracking · 2D Marker · Sensor Fusion · Piece Good · Conveyor

1 Introduction

The complexity of companies and their environment has increased over the last years. The causes are seen in the trend toward global markets and also more individualized products with a shorter life cycle [1, 2]. This particularly affects one of the important building blocks of supply chains and manufacturing environments: facility logistics systems. Optimizing the trade-off between short throughput times, a high schedule reliability, low WIP levels, and a high utilization of the system becomes more challenging [3, 4]. One classical solution to this dilemma is the use of automated systems. When properly dimensioned and highly utilized, such systems operate very efficiently and effectively. However, in the past years, the reputation of automated systems has suffered among businesses due to the high initial cost and long runtime they require. It is not uncommon that systems are planned for use periods of 15 years or more. The possible need to change those systems represents a high risk for businesses since changes in classical automated systems are often very expensive. Many promising approaches for new information and communication technologies have been developed in the past few years, especially decentralized systems based on software agents (often associated with the broader vision of the "Internet of Things" [5–7] and also as a specific vision for logistic networks [8]). This incorporates the development of the "Radio Frequency Identification" (RFID)

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technology as a major shift in the way data about logistical objects is managed. All these developments have one common goal: to make automated facility logistic systems easier to change and cost-effective in the long term.

In this paper, we address roller and belt conveyor systems as a typical form of automated transport and distribution of piece goods (parcel, bins, etc.) within a distribution center. Several intersection points redirect the piece goods to the desired destination. To perform this task, the exact position and sequence of all objects must be known. Today the identification of the conveyed object is detected at a so-called *Identification Point* (I-Point) at the interface between manual and automatic systems (shown in Fig. 1a). The relatively high cost causes limited installation of further identification equipment beyond this point. Within the automated system, this has the consequence that the sequence of objects must be controlled very carefully [9]. Any uncontrolled change will result in misordered data. The control system then acts according to false assumptions and transports the piece goods to unintended locations. Due to this fact, a number of problems occur that concern the setup of systems, re-starting after system failure, and manipulation of the piece good order. Therefore, a new system design that can provide a continuous identification and localization of objects is highly desirable—if it is economically justifiable.

In this paper, we propose a system that uses the advantages of both RFID and vision technology for tracking piece goods and controlling the intersection points in the material flow system. The identification and the piece good destination are obtained by RFID, globally for the whole system, respectively, for a bigger section (see Fig. 1b). The vision system realizes the localization and tracking of the piece goods mainly at the local intersection points. We use a particle filter tracking algorithm [10] utilizing features based on geometric models and integral histograms [11] applying

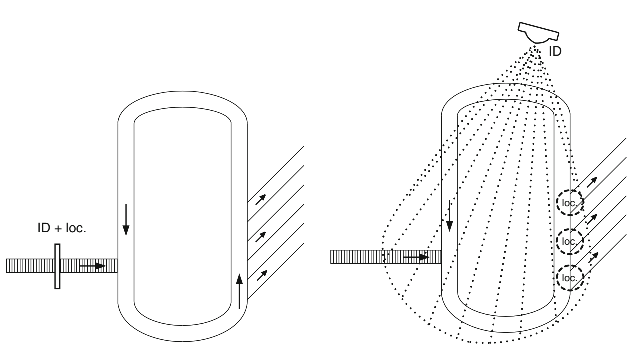


Fig. 1 Identification and localization at a (**a**) central identification point, (**b**) global identification via RFID for the entire system, respectively for a bigger section and localization by vision at local intersection points

just a single standard camera. Additionally, 2D visual markers [12, 13] are used for camera-based identification and comparison with the RFID information.

The task outlined above is structured in five sections. Following this introduction, the state of art is presented for RFID and vision technology in Sect. 2. Next, an overview of the conveyor scenario is given providing the basis for the following considerations (cf. Sect. 3). The core of the vision-based system for the tracking of bins and the marker readout is described in Sect. 4 and evaluated in Sect. 5. Based on these explanations, Sect. 6 deals with the integration of the given vision-based system in a combined approach with RFID technology. Finally, Sect. 7 recapitulates the main statements of the paper and gives an outlook on the future steps of development.

2 State of the art

Due to standardizations like the Electronic Product Code (EPC) [14], Radio Frequency Identification (RFID) technology increases the efficiency and productivity especially in the context of logistics and supply chains [15]. Today RFID can be used in closed loop bin (Returnable Transport Item) systems like mail sorting centers [16], food retail [17, 18], automotive [19], but also in single use applications. In 2007, the "International Air Transport Association" (IATA) investigated the performance of RFID technologies, examined a business case for the use in baggage handling [20], and developed a RFID implementation plan.

In current projects concerning the implementation of RFID in conveying or sorting systems (mail sorting, baggage handling, etc.), the traditional combination of auto identification and light barrier is still used and barcode readers are just substituted by RFID readers. Short reading distances (e.g., proximity coupling [21]) or damping down the antenna performance generates pseudo localization: the field strength is so limited that detection is equivalent to localization. So, in our opinion, the full potential of RFID solutions is not tapped.

Furthermore, several approaches for the localization of active and passive RFID-tags have been proposed in the past—often under the topic of "Real Time Localization Systems" (RTLS). For example, the system called LANDMARC uses the "Received Signal Strength" (RSS) [22]. In [23], the localization relies on the "Time Difference of Arrival" (TDOA). Mojix, an US-american company designed a real-time localization system called STAR, which is able to establish standard passive (UHF) RFID-Tags. The system architecture includes a single central receiver connected with up to 512 RFID-Tag excitation points called eNodes. By activating single eNodes, power is supplied to the passive RFID-Tags within its local environment. The accuracy of the system is close to one meter (depending on tag density, type of item, and on environment) [24]. Ubisense, developed at the University of Cambridge, is another commercial ultra wideband (UWB)-based localization system. In this application, again both TDOA and AOA are used. To be able to perform the latter, the reference units are equipped with antenna arrays. The guaranteed accuracy is 15 cm. Ubisense currently yields the best accuracy of all RFID-based indoor localization systems [25]. However, this performance requires high system cost [25], because each detectable object needs an expensive active transponder (5.8 GHz).

Because of the high cost or the missing accuracy and the likelihood of error due to signal absorption and indirect path in a conveyor belt environment consisting of various electronic and metallic objects, existing RFID systems are not sufficient for a reliable, precise, and cost-effective positioning and tracking of the piece goods (in sequence) and the control of intersection points of the conveying system.

However, computer vision systems based on single or multiple standard cameras offer an alternative way for accurate object positioning and tracking at low investment cost. Several standard tracking methods are surveyed in [26]. In context of logistics, the authors of [27] present a calibrated Multi-Camera vision system for real-time tracking of parcels moving on a special conveyor belt. This belt consists of several independently controlled and moved sub-belts to arrange a bunch of parcels into a single line. In the first stage, the dimensions of every parcel are computed by two calibrated cameras. In the second stage, four additional ceiling-mounted cameras track the corner points of the parcels using the well known Kanade-Lucas-Tomasi (KLT) Feature Tracker to extract the parcel position information which is then fed into the sub-belt controller. A similar system called "Visicon Singulator" has been presented by Siemens [28]. Due to the system's ability of setting the piece goods into an arbitrary orientation, additional components like barcode-scanners or ORC-readers for address arrays, etc. can be used.

Nevertheless, unlike RFID technology, vision-based systems are always depending on lighting conditions (luminance, lighting changes) and on an existing line of sight to the observed objects. To overcome the specific drawbacks of both systems and to maximize their potential, a combination of RFID and vision can be performed.

3 Setup

To develop the vision system, a realistic application scenario of bins transported on roller or belt conveyors is considered. Besides scenarios of straight or curved conveyors from different points of view, the most interesting scenario requires a routing decision at a switch. The chosen scenario is part of the testing facility at the chair of materials handling and warehousing in Dortmund, where especially challenging conveying and handling devices are implemented. Any component needed for this survey is contained within the selected area. This scenario is shown in Fig. 2. To decide in which direction bins, arriving at the switch, are routed, the sequence of the piece goods on the conveyor has to be known. Inside the RFID-antenna's range bins are detected via radio communication (which is in the actual setup emulated as a given database), but their exact positions and order cannot be determined. Applying a visual tracking algorithm, each bin's trajectory and occupied region within every image can be evaluated over time from a sequence of camera images. By reading visual markers attached to the piece goods from this occupied image regions, the order can be evaluated and a routing decision is possible. Limiting the reading of visual markers only to occupied image regions has a great advantage regarding performance and reliability compared to a complete processing of every image within the sequence. Bins of the considered type in this work are shown in Fig. 3, and the attached marker is shown enlarged. Internationally standardized Data-Matrix and Quick-Response Marker are used in this work [12, 13]. Figure 4 shows one instance of each marker type.

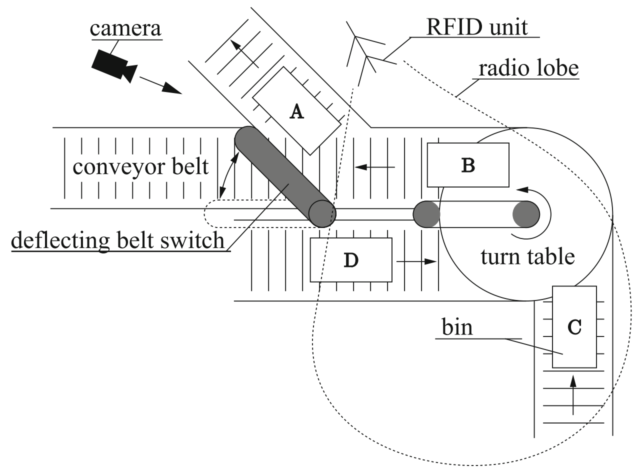


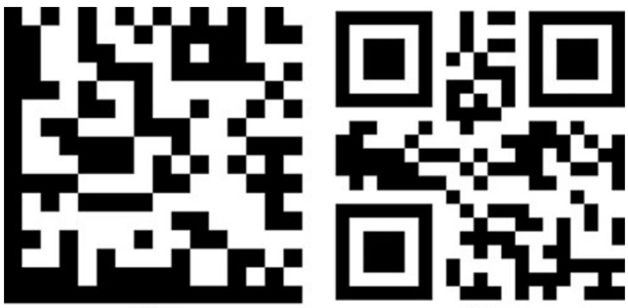
Fig. 2 Overview of the conveyor scenario representing a combination of a vision-based system and a RFID system

4 Vision-based tracking

The vision system is divided into two dependent components. The system's first stage detects and tracks piece goods (cf. Sect. 4.1) employing features based on dynamic models (cf. Sect. 4.2), while the second stage detects and reads the marker, where a piece good is tracked (cf. Sect. 4.3).

Fig. 3 Visualization of the (**a**) conveyor scenario viewing bins of the considered type and (**b**) the attached marker

(a) Conveyor scenario **(b)** Bin with attached DM marker



(a) **(b)**

Fig. 4 Visualization of a (**a**) Data-Matrix and (**b**) Quick-Response marker

To improve the image data acquired by a standard camera, image enhancement techniques are applied according to the requirements of the concrete camera. Those enhancement techniques are for example smoothing of noisy images [29] or deinterlacing methods to obtain a full image from half images containing only odd or even pixel lines [30]. In this work, an intraframe deinterlacing method proved to generate the best results for marker identification. It calculates missing lines as arithmetic mean of neighboring lines and requires little computational time.

4.1 Object tracking

Tracking of objects over image sequences means searching for corresponding objects in successive images. By predicting the dynamic movements of objects, the image area that has to be examined for the occurrence of the object is restricted. The predicted position is then corrected by comparing its image features to characteristic features of the tracked object. The characteristic features examined in this work are a shape-based feature represented by a grid model and a color-based feature represented by color histograms. The procedure to extract these dynamic features is explained in more detail in Sect. 4.2.

The foundation of probabilistic tracking algorithms is the Bayesian filter algorithm [31]. It calculates the object's state $\mathbf{X}_t \in \mathbb{R}^n$ at time step t which is represented as probability distribution over the n-dimensional state space $\mathbb{R}^n$. The system's belief $Bel(\mathbf{X}_t)$ of the actual object state is calculated in two steps: the prediction and the correction step.

The prediction step predicts the object state $\hat{Bel}(\mathbf{X}_t)$ based on the previous object state $Bel(\mathbf{X}_{t-1})$ and a model of the object's dynamic, the dynamical model $\Pr(\mathbf{X}_t|\mathbf{X}_{t-1})$ as:

$$\hat{Bel}(\mathbf{X}_t) = \int \Pr(\mathbf{X}_t|\mathbf{X}_{t-1}) Bel(\mathbf{X}_{t-1}) d\mathbf{X}_{t-1}.$$

The prediction $\hat{Bel}(\mathbf{X}_t)$ is corrected in the second step by multiplication with an observation model $\Pr(\mathbf{Z}_t|\mathbf{X}_t)$, which depends on the observed image features $\mathbf{Z}_t$ and a normalization constant η:

$$Bel(\mathbf{X}_t) = \eta \Pr(\mathbf{Z}_t|\mathbf{X}_t)\hat{Bel}(\mathbf{X}_t).$$

For example, components of the object's state represent the object's position in some coordinate system.

The Bayesian filter algorithm cannot be implemented directly without constraining possible applications. Therefore, implementations have to approximate it. A well-established approximation is the particle filter algorithm, which approximates the considered probability distribution by a set $\mathcal{X}_t = \{\mathbf{x}_t^{[i]} | i = 1, \ldots, N\}$ of samples $\mathbf{x}_t^{[i]}$ drawn from this distribution [10]. The convention is taken that particles of a sample set at time step t are enumerated by a superscript i. In an iteration of the algorithm, samples are drawn from the distribution $Bel(\mathbf{X}_{t-1})$ and moved through the state space by the dynamic model. The distribution $\hat{Bel}(\mathbf{X}_t)$ of moved samples is corrected by weighting samples with so-called importance factors $w_t^{[i]} = \eta \Pr(\mathbf{Z}_t|\mathbf{x}_t^{[i]})$. The weighted sample set then represents the distribution $Bel(\mathbf{X}_t)$. The whole process is called importance sampling, a tuples $\langle x_t^{[i]}, w_t^{[i]} \rangle$ of sample value and weight is called particle and $\mathcal{X}_t = \{\langle \mathbf{x}_\mathbf{t}^{[\mathbf{i}]}, \mathbf{w}_\mathbf{t}^{[\mathbf{i}]} \rangle | i = 1, \ldots, N\}$ is called particle set.

If at the beginning of every iteration a resampling step takes place, the resulting particle filter is a so-called Condensation algorithm [10]. Resampling generates a particle set A from another particle set B, while both sets have the same cardinality. Therefore, particles from B are drawn with repetition according to their weights. Generally, a particle is drawn more often if its weight is high. The particle set A represents approximately the same distribution as the particle set B, although the weights of particles in set A are uniformly distributed.

The condensation algorithm needs to correct its prediction by weighting particles according to the similarity between the tracked object's appearance and the corresponding image data within a sequence of images. Different types of features can be used to express the similarity. The next section introduces the features based on dynamic models.

4.2 Dynamic models

The appearance of the tracked objects can vary over time within the image sequence: objects can appear in different perspectives while moving through 3D space, or the observed colors can change due to lighting changes, shadows, partial occlusions, or noise. Thus, using features based on dynamic models is adjustable to these changes and improves tracking performance by adapting the dynamic model's parameters dynamically over time. Grid-model and color-model based features are explained in the following.

A grid model is used to characterize the piece good's shape. Characteristically for piece goods, represented as simple cuboids, are the aspect ratios of the piece good's side lengths. By defining the piece good's width as 1, the grid model is defined by the aspect ratio between width and height and by the aspect ratio between width and length. The piece good's appearance in the image is determined by scaling and rotating the grid model. In this way, perspective changes due to piece good's movements are concerned dynamically by the model. After projecting the obtained grid model into the two-dimensional image plane, its similarity to the piece good's edge representation is calculated by summing up distances of model edge pixels to piece good's edge pixels obtained by a distance transformation. Normalized distance sums are used as particle weights.

A color-based feature to correct the algorithm's prediction uses histograms. A histogram counts pixels for different color ranges, which results in a discrete color distribution characterizing the considered image area. Given that the color of objects depends on the scene's lighting, the model histogram is not predefined. The object's histogram is calculated and saved when the object is first detected. It is adapted over time to handle changing lighting conditions. To obtain all particle weights, one histogram per particle has to be calculated, and because of the large number of particles, this calculation has to be done efficiently. Integral histograms are used as an efficient way to calculate many histograms in one image [11]. The integral histogram is calculated once per image and enables histogram calculation in constant time for rectangular areas within the original image. Particle weights are given by the Bhattacharyya distance [32] between the object's and the particle's histogram.

Any tracked object has to be detected in the first step. The detected object is used to initialize a tracking algorithm (cf. Fig. 5). Object detection is a large field of research, but the detection always depends on characteristic features of the objects to be detected. Because all piece goods of interest in the logistical scenario are in motion, this can be used to detect them by difference image or background subtraction algorithms, which are known to be at low computational cost. After an initial object detection, the tracking algorithm determines the rectangular region (region of interest) containing the tracked object within each image. The next section describes how visual markers can be found and identified within that region of interest.

4.3 Piece good identification

To identify tracked piece goods, the attached two-dimensional marker has to be read. Data Matrix and Quick Response markers contain finder patterns, to determine where markers are present and how a found marker is oriented in space. Finder patterns are marked red in Fig. 6.

Markers are found in edge-images by searching for closed contours describing the outline of a marker's finder pattern. Contours are approximated to obtain straight lines, which can be checked for some geometrical constraints. A single part of a Quick Response finder pattern has to consist of three nested squares, with given area ratios.

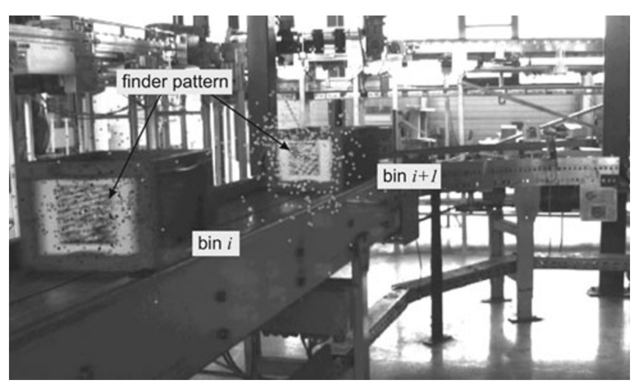


Fig. 5 Distribution of particles during tracking of two bins. The expected values are each identified by a marker (finder pattern)

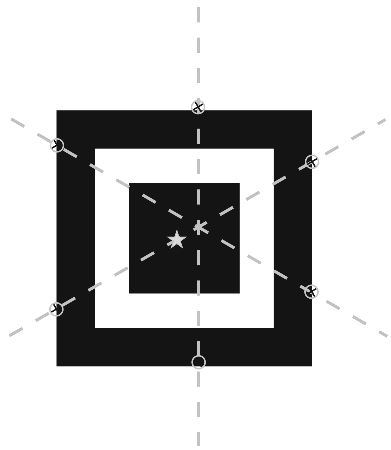


Fig. 6 Finder pattern of a Quick Response marker (cf. Fig. 5). The midpoint of the finder pattern determined by a contour detection is marked by the intersection of the scanlines. The mean square error of the three scanlines is represented by the asterisk

Locations of found finder patterns are refined by scanning pixel lines and searching for color changes from white to black and vice versa.

If the marker is located, its position and size are known, so a grid of sample points can be laid over the found image area. At every grid point, a module of the marker can be read. The sample grid is perspectively distorted according to the synchronization pattern of the marker. The synchronization pattern are represented by the circles in Fig. 6 enables the system to deal with marker distortions. The read marker data is finally compared to the RFID-based marker data, to detect reading errors early.

5 Evaluation

The following evaluation of the visual tracking system for a material flow system, as described in the previous section, is divided into aspects of real tracking and marker readout. Besides the general issues concerning the quality of tracking, a focus is on using camera types of different price segments. An interesting question is whether it would be able to reconcile economic efficiency with the quality of cameras. Prior to the evaluation starting, the test cases and different cameras are described in the following section.

5.1 Test cases

The basic experimental setup is shown schematically in Fig. 2. It is visualized that the bins will be utilized by a turn table toward a deflecting belt switch. In addition to the RFID unit, the positioning of a camera for the visual system is shown. This test case permits a verification of the real bin tracking and also the marker detection with regard to making a decision (at the deflecting belt switch). Based on these settings, it is possible to distinguish within the verification process among the parameters of

- camera type,
- camera position,
- marker type, and
- object distance.

To evaluate the influence of different cameras, three models of different camera classes are used. The low-priced segment is represented by the “Creative Labs—Live! Cam Optia AF” webcam with CMOS-sensor and a resolution of 800 × 600 pixels. A high-resolution mode reduces the frame rate from 30 fps (frames per second) to 5 fps at a resolution of 1600 × 1200 pixels. The high-cost segment is represented by two cameras using CCD-sensors. By progressive scanning, the first camera “DFK 31BU03” distributed by “The Imaging Source” takes images with a resolution of 1024 × 768 pixels at a frame rate of 15 fps, while the second camera “Sony—EVI-D31” uses interlaced scanning to obtain images with a resolution of 720 × 576 pixels at a frame rate of 25 fps.

For the following evaluation, there were about 100 test sequences available. A sequence covers the path of one bin through the scene—this is discussed in the following section.

5.2 Testing of vision-based tracking and marker detection

The first relevant aspect of evaluating the tracking system is the distance between the camera and the region of interest. Figure 7 shows for this case the time up to the first marker detection itemized into the distance between camera and the bin. The box plot indicates clearly that the marker detection benefits from a close camera position and therefore a large image of the marker. It should be noted that, in spite of a long distance between the camera and the marker, the marker detection occurs in time. In addition, the angular freedom of the deflecting belt switch is obtained until 0.65 units of time and therefore definitely before first marker detection.

To determine the detection success rate for the markers, a quantitative comparison of the detection rates relating to the camera type (cf. Fig. 8a) and the marker types (cf. Fig. 8b) is graphically represented by box-and-whisker plots [33]. As can be seen in Fig. 8a, the resolution if the images is a decisive factor for the detection. By comparing the two resolutions of the Live! Cam, it appears that the resolution of 1600 × 1200 pixels is considerably better than the alternatives—in spite of a frame rate of just 5 fps. This assessment was confirmed by the detection rates of the two additional cameras. Considering the camera resolution,

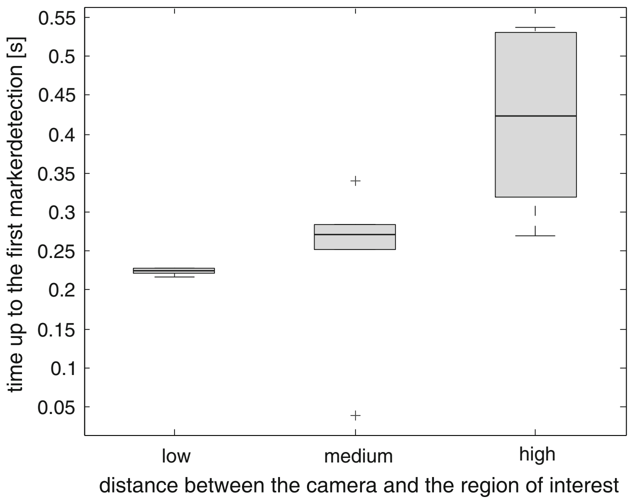


Fig. 7 Comparison of different distances between the camera and the region of interest. The distinction is drawn between low (up to 1 m), medium (ca. 2 m), and high (from 3 m)

the detection rates of the cameras “DFK 31BU03” and “Sony—EVI-D31” are within the detection range of the two specifications of the Live! Cam. The second aspect for estimation of quality of the marker detection is the detection rate, distinguishing between two different marker types: Data Matrix and Quick Response (cf. Fig. 8b). It should be noted that the analysis refers only to the point in time unless the markers are in the visual range of the camera. It is readily identifiable that evaluations of the Data Matrix show the maximum higher detection rate, but at the same time a higher scattering. In case of the Quick Response markers, a lower average detection rate is given. But the minimal detection rate is below the detection rate of the Data Matrix Code.

Besides the pure marker detection, the readout of the marker information is of great interest for material flow systems. To allow an evaluation of the readout, the actual encoded identification code (by the marker) is given, and therewith to calculate the Hamming distance [34] to the read identification. This equates accurately the situation of transmitted information of markers by the RFID systems. To be consistent between the visual (image processing) system and the RFID system, the Hamming distance is calculated between all RFID-based identification code and the visual readout. The combination with the minimum Hamming distance is accepted as identification. The absolute value Hamming distance is a degree of quality of the marker reader. By giving the real identification, this approach allows to simulate a situation similar to reality in material flow systems.

The box-and-whisker plot in Fig. 9 shows the percentage of misread markers distinguished between different types of markers (cf. Fig. 2). It is quite evident that the

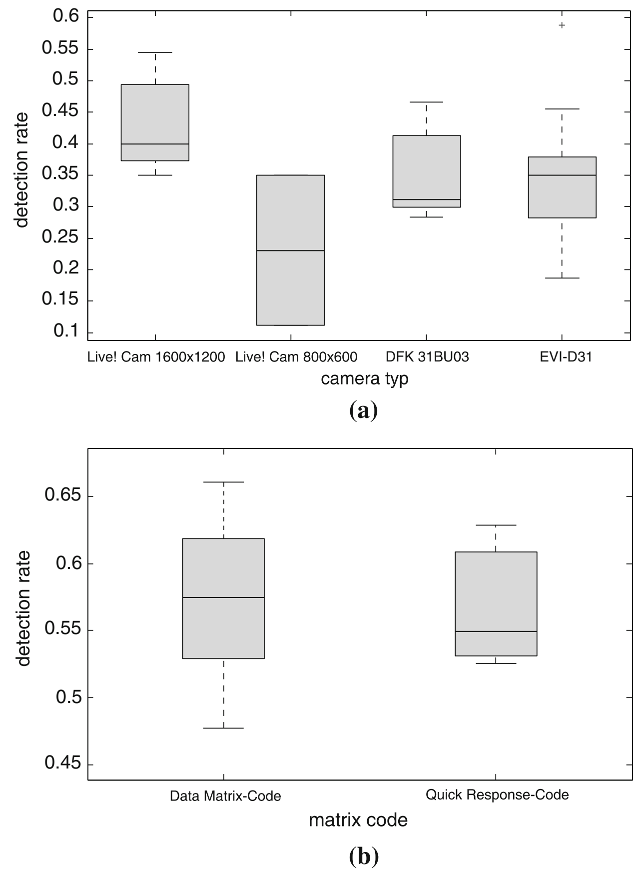


Fig. 8 A quantitative comparison of the detection rates relating to (**a**) the camera type and (**b**) the marker types

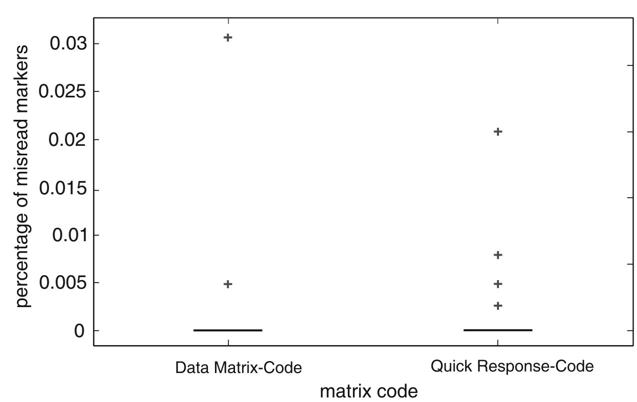


Fig. 9 A quantitative comparison of markers considering the percentage of misread markers

readout is nearly error free. There are only a few misread markers (cf. the crosses in Fig. 9). The highest fraction of misread markers is a total of 8 out of 441 for the Data Matrix Code.

Summarizing the current state of evaluation, it can be stated that the presented visual system for readout of the markers satisfies the requirements of the current use case. This is the basis for a combined material flow system of

RFID technology and visual (image processing based) marker reader, which is described in the following section.

6 Combining vision and RFID

Due to the proposed vision-based identification, there are now two possible ways to obtain the ID of a piece good, namely by reading out the marker data or the data stored on the RFID-tag. Several advantages can be gained from this additional information. For example, the ID extracted from the visual marker can be compared to the IDs of all actual existing objects within the current production cycle. If there is no match, an error within the vision system can be assumed (e.g., failure in reading the marker because of occlusion or noise or even false marker detection). On the other hand, an error in the database of the production cycle is possible, too. Furthermore, the combination of both systems serves as security warning. Notice that because of potentially unequal available amount of storable data in the visual marker and the RFID-tag, these two IDs are not necessarily identical, as long as each ID is unique within the considered domain. In most cases, a database is already utilized to store the association of IDs and real objects, so this database can also manage the mapping between both IDs in the case of inequality.

Another advantage is the known accurate position and order of the identified piece goods that can be directly carried out from the tracking algorithm presented in Sect. 4.1. Compared to RFID-based piece good localization precision, a much more reliable routing at conveyors intersection points is feasible. Faster conveyor systems, smaller piece good intervals and, as a consequence, higher efficiency are possible due to more precise location information at intersection points (see Fig. 2).

7 Conclusions

In this paper, we presented the motivation and a novel approach for marker-based tracking in material flow systems. This depends on a visual unit and adapted computer-graphics methods. The main focus of attention is on the goal to combine a visual and RFID system. In a combined application, it would be possible to resolve errors using the marker readout with the assistance of the given marker list from the RFID unit. After evaluation, it became clear that time restrictions for the marker readout were duly kept and the readout unit for the marker offers a high reliability. But even in the case of insufficient information from the RFID system for an error correction, the inherent error correction of the marker can be used to identify and resolve possible faults.

From a logistics point of view, several problems linked with material flow systems could be rectified. For the same reason system setup, re-starting after failure and manipulation of piece good order cause problems: data being misordered through system failure or uncontrolled change of sequence. Within the proposed system design, every piece good is localized and identified at every intersection. So the sequence of the objects no longer has to be controlled.

As already mentioned in Sect. 6, combining a piece good's ID achieved from both the vision and RFID system can be used to detect system failures, inconsistencies, problems, etc. In future work, the handling of these issues has to be explored. For example, comparing the IDs read out by vision with identification from RFID, scenarios such as a piece good falling off the conveyor could be detected—an ID is permanently received but never identified by the vision system within the RFID reader's range (cf. Fig. 1b). Also the identification by the vision system without the corresponding identification by RFID could be used as an indication for an empty battery in case of active RFID-Tags. Thus, the sensor fusion of camera and RFID tag, in combination with efficient software applications, promises many additional monitoring options in material flow systems.

Due to the need of continuous (at least at every intersection) identification and localization of objects in the material flow, costs are a key issue en route to the Internet of Things. We found one way to solve the mentioned problems. Beyond other techniques, the proposed solution is cost efficient as well as reliable. Hence, our results contributed an economically justifiable solution toward future automated facility logistics system.

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