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Supervised and unsupervised learning in vision-guided robotic bin picking applications for mixed-model assembly

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Abstract

Mixed-model assembly usually involves numerous component variants that require effective materials supply. Here, picking activities are often performed manually, but the prospect of robotics for bin picking has potential to improve quality while reducing man-hour consumption. Robots can make use of vision systems to learn how to perform their tasks. This paper aims to understand the differences in two learning approaches, supervised learning, and unsupervised learning. An experiment containing engineering preparation time (EPT) and recognition quality (RQ) is performed. The findings show an improved RQ but longer EPT with a supervised compared to an unsupervised approach.

Keywords: Bin picking; Order picking; Kit preparation; Robotics; Materials Handling

1. Introduction

Mixed-model assembly usually involves numerous component variants that require effective materials supply [1]. Picking and sorting activities are often performed in warehouses or at logistics workspaces, e.g. as kit preparation, in order to arrange materials for the assembly processes, and high levels of quality, flexibility, and productivity is essential.

Picking processes involve extensive material handling work, but it also involves considerable engineering work with keeping the process up to date with changes in the product structure and SKU (Stock-Keeping Unit) assortment. The engineering work is critical for normal operation of the picking process, and it is important that the engineers are equipped with effective tools to this end [2].

Using robotics for picking and sorting activities has the potential to improve quality and productivity [3]. While robots tend to perform effectively in deterministic settings where all critical factors are known before task execution, the application of robots to picking activities usually implies dealing with materials arranged as received from suppliers, in form of picking and sorting of randomly organized materials inside bins – often referred to as *bin picking* [4]. Bin picking is a challenge in most robotic applications, owing to the precise information needed about the items position and orientation for the robot to effectively perform its task.

Vision systems – referring to a scanner for taking 2D or 3D images of objects, and a software for analyzing the images to extract useful information – can be an effective support for robotic bin picking applications, whereby robots can learn to recognize components in order to perform their tasks. Robots can learn in accordance with two principal approaches: supervised and unsupervised. With the former, a person shows the robot what to recognize, for example by means of indicating the shapes of items to pick on a set of images, a process hereon forth denoted as *annotation*. With the latter, the learning takes place automatically by means of a deep learning model which is capable of distinguishing

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objects and object features, ideally without the support of a person.

While introducing robotics for picking activities is appealing from a standpoint of improved quality and productivity, it is crucial to consider the work involved with setting up and maintaining normal operation of the process. With robot-supported applications, reconfigurability of tasks and resources [5] are key from both an operational and from an organisational standpoint. Supervised and unsupervised learning presents two different approaches that may affect both operational performance and the engineering work required to maintain the process, which, in turn, play key roles for reconfigurability of robot tasks and collaboration between humans and robots. Previous research presents little guidance on which learning approach to use, and what the associated effects are of using either option. Therefore, this paper aims to understand the differences in two learning approaches: supervised learning and unsupervised learning, with respect to picking and sorting activities in robotic bin picking applications.

The paper presents a laboratory experiment containing *engineering preparation time* and *recognition quality* with respect to supervised and unsupervised learning as means of training for vision systems to support bin picking applications. In the next section, the method is presented, followed by a presentation of the results. Finally, the results are discussed, and conclusions are formulated.

2. Frame of reference and study objective

Certain aspects within the area of industry 4.0 regarding kit preparation have been dealt with in previous research, such as human factors and cognitive automation of kitting processes, [6], material feeding [7] and digital twins for supply chain [7].

Several studies have addressed the picking information system and cognitive automation solutions used to support manual kit preparation [6], [8-10]. All these studies uses time efficiency of the picker as the main KPI, the studies also consider picking quality, in terms of how many picking errors are made. An economic comparison of different paperless picking information systems in a warehouse order picking context has been executed [6]. In [8], focus was on comparisons with respect to the use of different picking information systems, e.g. pick-by-light, pick-by-voice, and pick-by-HUD, while [9] considered the use of augmented reality to support manual kit preparation. In [10], a time-efficiency and picking quality comparison was made between confirmation methods in manual kit preparation.

Increased physical automation, e.g. robotic kit preparation, was addressed more than twenty years ago (e.g. [11,12]) but has not yet gained widespread application within industry. It is possible to design kit preparation in collaborative setups, where a robot and a human operator work together. One potential advantage of collaborative setups is that the flexibility of the human operator may be used to manage some of the complexity in the system. Collaborative setups have been addressed in several publications, considering different perspectives, such as safety, time efficiency, and ergonomics (e.g. [13-16]). Fully automated picking entails multiple challenges, including finding suitable gripper types to match the component characteristics [17-19]. Another important challenge is to get the robot to match the location and the orientation of the items to be picked. Unless the orientation of the items is predetermined and fix, some mechanism is required to support the robot in this.

Robot picking of items that are randomly oriented inside a bin is often referred to as bin picking and there are numerous technologies that can support this sort of process [20]. The use of vision systems to support bin picking has received some attention, most of which focuses on technical aspects in the design of such systems. [21] propose a visual recognition system for learning-based bin-picking. [22] propose a deep learning approach for image completion and masking, which should be applied in robotic bin picking. [23] focus on picking of textureless planar-faced objects propose a depth-based vision-guided robot bin-picking system that utilises a deep convolutional neural network model.

While there are publications that address certain technical aspects of automated bin picking with regard to machine learning, less research seems to have taken perspectives directly relevant to those production or logistics practitioners who may apply robotic picking in industrial applications, such as kit preparation, and who are facing choices of which type of system to choose. To the best of our knowledge, there is no study available that directly compares supervised and unsupervised learning in vision-guided robotic bin picking applications. An effective bin picking process relies on several aspects to synergise, where the vision system plays one of the key roles. However, the robot's path planning is also essential, as is the type of gripper used, for the robot to successfully be able to grasp components. Therefore, in order to carry out a fair comparison of the two learning approaches, the focus with the experiment in this paper is set on the quality of vision results, in terms of recognition quality, and on the time involved in producing the results, in terms of engineering preparation time. The robot's ability to grasp components are outside the scope of this research, as there are many more factors that come into play besides the vision results.

Engineering preparation for manual kit preparation in terms of task descriptions and ergonomic analysis can be very time consuming and is often made based on experiences. Production planners tend to neglect actions proposed by system planners because they are unwilling to trust techniques they know are inadequate [24]. Detailed planning or optimisation also becomes unattainable if planning systems use inaccurate data [25]. Optimisation can become meaningful, and less manual work will be needed in the planning and control process [26]. By using more automatic solutions with help of AI and optimisation algorithms, the time for preparation could decrease and the picking quality can increase.

3. Method

An experiment was designed to compare the engineering preparation time and the recognition accuracy of two learning approaches: supervised and unsupervised. The two approaches were compered in terms of five different categories and criteria with respect to the ability of the vision system to provide a robot manipulator with reliable information in order to carry out bin picking of components in an application for kit preparation. The criteria used for distinguishing each of the categories are shown in Table 1.

Table 1. Criteria and categories used for analysing recognition results

Category	Criteria
Detected	An object has been indicated as detected by a square in the 2D-results, and by 3-axis spatial coordinates on the object in the 3D-results.
Undetected	The object is clearly visible in the 2D- and 3D-scans but has not been indicated as a detected object.
Correct detected objects	A detected object has been assigned 3-axis spatial coordinates at its center of volume that is aligned with key shape features of the object.
Partially correct detected objects	A detected object has been assigned 3-axis spatial coordinates at its center of volume, but the coordinates are randomly aligned with key shape features of the object for different objects of the same type.
Incorrect detected objects	A detected object has been assigned 3-axis spatial coordinates that are not centered at the object's center of volume, and that is randomly aligned with key shape features of the object for different objects of the same type.

The analysis was carried out by statistical comparison of the engineering preparation time and the grasping accuracy between the two learning approaches.

3.1 Experiment set-up

A setup for comparing the effects of two learning approaches for vision systems with respect to kit preparation was built. The setup simulated a process for kit preparation, whereby a 3D-scanner was positioned above a rack with bins that contained the components. The setup involved a Solomon SLM 3DRBP-0501C 3D-scanner and the accompanying software Accupick v.3.1.2. The rack configuration, in terms of the tilt and height of the shelf levels, was adjusted with respect to the reach of a robot arm positioned in front of the rack, see Figure 1. The robot's reach was tested in order to ensure that robot could reach inside each bin presented in the rack, and the scanner's position relative to the rack was adjusted, in terms of its height, tilt, and position relative to the rack center, so that all nine bins in the rack could be scanned successfully in a single scan.

3.2 Component selection

Three components were selected to be analyzed in the experiment. The selection criteria were to include components that represented different recognition requirements and different geometry challenges in terms of graspability (this is out of scoop for this paper). Hence, the components differed in terms of their visual characteristics (see Figure 2), but were all light in terms of weight, and all could be picked by means of a two-finger servo-electric gripper.

As shown in Figure 2, Component 1 had a simple shape and, in terms of orientation, only required differentiation between its long and short sides, in addition to knowledge about its center of volume. Component 2 was cylindrical and slightly more complex, where four small holes penetrated the component between its planar faces. Pairwise, the four holes were positioned with different distances apart. Component 2 had an orientation requirement with respect to the four holes, in addition to knowledge of its center of volume. Component 3 was more complex and had to be grasped by its end. Furthermore, multiple items of component 3 were prone to tangle inside the bin.

Fig. 1. Overview of the experiment setup

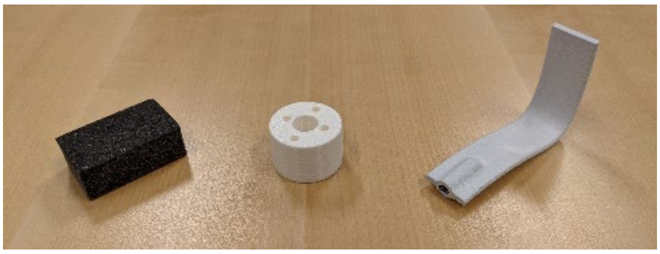

Fig. 2. The three component types considered: Component 1 (left), Component 2 (middle), Component 3 (right)

3.3 Engineering preparation activities

With respect to engineering preparation time, the three components were prepared for bin picking by means of the two learning approaches. For each of the three components, the time for performing the activities involved in preparing the vision system to recognize the components was measured, using both learning approaches. The engineering preparation time was estimated as the total time required for each component and learning approach. For each component, the measurement of engineering preparation time was started the moment the engineer grabbed a bin with the components that the vision system should learn.

The activities involved with the *supervised learning approach* were as follows:

1. Grab bin and position bin in field-of-view of the scanner (photography activity)
2. Acquire 25 pictures of the bin contents, and shuffle the contents between each picture (photography activity)
3. Determine 2D geometric figure approximation to use for annotation of principal orientations of the component in the vision-system software (annotation activity)
4. Annotate all instances of the principal orientations (one annotation class for each principal orientation) (annotation activity)

5. Generate deep-learning model (training activity)
6. Test and verify the learning results by performing recognition of one of the pictures in the input picture set (validation activity)
7. In case of failed verification, readjust the settings until the verification passed (validation activity)

With the *unsupervised learning approach*, the activities were as follows:

1. Test and verify the learning results by performing a recognition on the bin to pick from (validation activity)
2. In case of failed verification, readjust the settings until the verification passes (validation activity)

With the supervised approach, the final step, in terms of readjusting the settings if the verification failed, involved checking the annotations and fixing any errors, adjusting the region of interest, and then regenerating the deep learning model. With the unsupervised approach, readjusting the settings only involved adjusting the region of interest.

3.4 Recognition settings

With recognition quality, vision analysis was performed five times on each of the three bins with the supervised and unsupervised approaches, respectively. Here, 3 bins, with 30 components of one of the component types in each bin, were positioned on the middle shelf level in the three-level box rack. The runs were performed alternatively between the two learning approaches, and the components inside each bin were shuffled between each pair of pictures. Hence, for each of the two modes, the same five random shuffling of the components inside each bin were scanned.

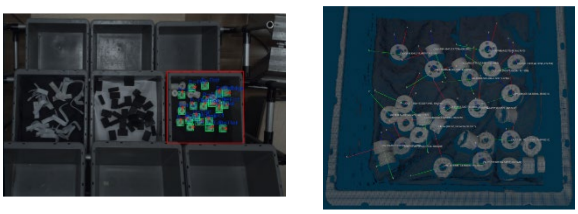

Fig. 3. Example of exported 2D- (left) and 3D-results (right)

For the analysis, the 2D- and 3D recognition results were exported, as shown in Figure 3. A first check was performed on basis of the 2D-results and subsequently verified by a detailed examination of the 3D-results. The number of detected objects, undetected objects, correct detected objects, partially correct detected objects, and incorrect detected objects were noted for each experiment setting.

4. Results

This section presents the results with respect to engineering preparation time and recognition quality for the two learning approaches.

4.1 Engineering preparation time

The time required for the vision-system to learn to recognise each of the three component types is shown in Figure 4.

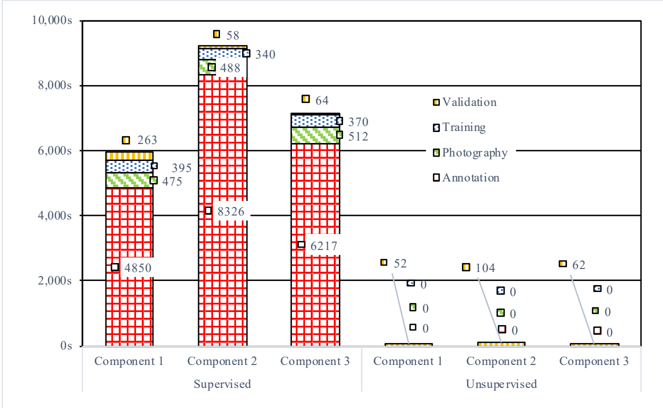

Fig. 4. Engineering preparation time [s] associated with the two learning approaches

As **Figure 4** shows, most of the engineering preparation time associated with supervised learning is spent on performing annotation. Here, the specific annotation tool used plays a critical role for the time required, as does the experience level of the user who performs the annotations.

The annotation time shows a substantial variability among the component types. This variability originates from the different annotation procedures used for each of the components. Here, two principal orientations were defined for both component 1 and component 2, and, with component 2, the flat orientation also had an orientation requirement. With component 3, there was only one principal orientation by which picking would be possible. However, the total number of annotations for each of the more frequent classes – flat for component 1 and 2 – matched with the number of annotations for component 3.

In conclusion, the results in Figure 4 show a stark contrast between the supervised and the unsupervised approach with respect to engineering preparation time.

4.2 Recognition quality

The recognition quality results, shown in Figure 5, show important differences between the two learning approaches.

With respect to detection, the unsupervised approach was more effective at distinguishing objects inside the scanner's field of view. Here, in most of the pictures, all the components within the field of view were identified as either one or several objects. However, many times several objects were detected as single object, where sometimes the separate objects were detected individually as well as in a group-object. In the 3D-results, this had the effect of creating several 3D-spatial coordinates which appeared to float in the air, or that was positioned between components, which is problematic for robot picking.

As can be seen in Figure 5, the unsupervised approach had very few components it was unable to detect, but on the other hand had a greater number of partially correct and incorrect detections. Here, an outlier is component 3, where the unsupervised approach showed a larger number of undetected objects, as well as a high incorrect detection rate. This was because the detection results grouped many of the components together and missed that the groups were composed of several smaller objects. However, some components were still identified correctly, and hence would be graspable. With component 2, the unsupervised approach was able to detect many of the components partially correct, meaning that the orientation of the spatial coordinates was wrong, but that the coordinates were centered on the center of volume. This also occurred for some of the components of type component 3. These components would be graspable in a kitting scenario, but their orientation would not be possible to control when the components are placed in the kit. With component 1, the unsupervised approach resulted in more correct detections than did the supervised approach. This likely due to the simplicity of the component 1 geometry.

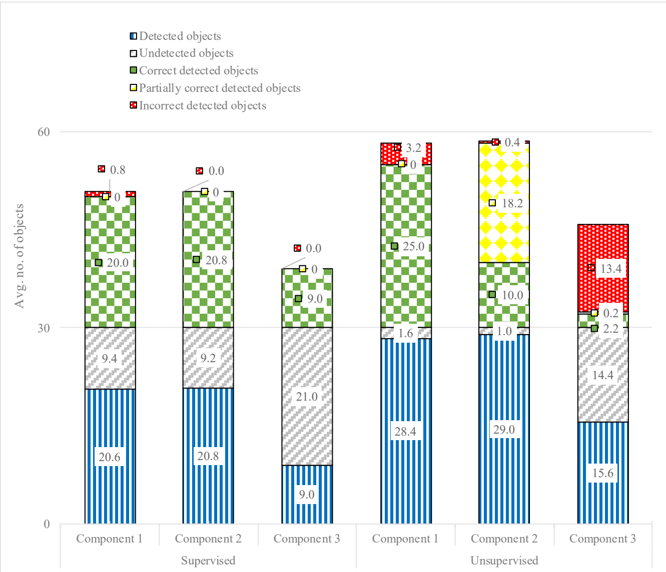

Fig. 5. Recognition results for the two learning approaches

With the supervised approach, there was generally fewer objects detected in each image, but the detections were correct to a greater extent. With component 3, only nine objects were detected on average, but all detections were accurately assigned with coordinates that would allow successful robot grasping.

5. Discussion and future work

The paper has presented an experiment dealing with engineering preparation time and recognition accuracy for two different learning approaches for a vision-system in a robotic bin picking application. This is important in industry, as it plays an important role for reconfigurability of automated processes.

The experiment involved specific types of technology and equipment, in terms of a 3D scanner, and a software for robot-vision. Furthermore, three component types with variable characteristics were considered. It is, therefore, of interest for further studies to also account for other variants of the technology and equipment, to form a complete and generalizable overview of how learning approaches affect reconfigurability.

The paper contributes to the literature in terms of demonstrating a hands-on example of the effects from two principally different learning approaches for vision systems, with respect to engineering preparation time and grasping accuracy. As the paper demonstrates, there are distinct operational effects from the choice of learning approach to apply when dealing with automated material handling.

The results highlight a tradeoff between engineering preparation time and recognition quality with respect to the learning approach, indicating that the two approaches can be beneficial in different situations. Supervised learning, which was associated with substantially longer engineering preparation time and higher recognition quality, is likely the more suitable approach in less dynamic settings, such as when products are produced in high volumes with less variety, and where the product assortment, in terms of product life cycles, is more stable over time. This is typical in many assembly systems but can also be achieved in more dynamic environments where a product structure is available, by assigning high-runner parts to the automated process.

The supervised approach considered in the paper could lend opportunity for generation and post-processing of the training model. Here, it is possible to generate annotations automatically from CAD-models that can be used for supervised learning, which likely would reduce the engineering preparation time. Furthermore, for enhanced detection, and the ability to generate custom pick-points offset from the object center-of-volume, it is possible to match the point clouds with a reference model of the object, in line with the approach described by [27]. Here, the reference model can be derived from a CAD-file or from a high-quality 3D-scan of the object.

While the paper accounts for operational effects of two learning approaches as associated with an automated process, the results also have implications for hybrid systems, whereby humans and robots work together [1]. A key for hybrid systems is flexibility, whereby humans and robots can support each other, and it is crucial that the robot can perform its tasks effectively and with high precision. Here, it is likely beneficial to employ a supervised approach, to ensure predictability in the robot's actions, which otherwise could lead to interference in the collaboration. With stochastic order patterns and volume fluctuations, picking robots could support a human workforce in handling the volume fluctuations. Here, it is important that the robots can be deployed quickly and making use of unsupervised learning could be suitable. This, of course, implies high requirements on the software infrastructure, where flexibility is key. An agent- and role-based planning approach that allows for strengths of both human and robot operators to be realized is important for achieving effective collaboration in the collaborative materials handling process [28].

A natural extension of the presented research is to compare the supervised and the unsupervised approach with respect to bin picking of components in a kit preparation application. However, in addition to the focus of this paper, this would also need account for the relationship between the type of gripper used and the component characteristics, as noted by [29]. Furthermore, how to deal with components that are positioned close to the bin wall, or components that are entangled with each other, must also be accounted for. Moreover, it may well be the case that different gripper types are more suitable depending on the principal orientation of the component to be picked – i.e., in terms of recognition, the recognition class.

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