An Automated Picking Workstation for Healthcare Applications

Abstract – The costs associated with the management of healthcare systems have been subject to continuous scrutiny for some time now, with a view to reducing them without affecting the quality as perceived by final users. A number of different solutions have arisen based on centralisation of healthcare services and investments in Information Technology (IT). One such example is centralised management of pharmaceuticals among a group of hospitals which is then incorporated into the different steps of the automation supply chain. This paper focuses on a new picking workstation available for insertion in automated pharmaceutical distribution centres and which is capable of replacing manual workstations and bringing about improvements in working time. The workstation described uses a sophisticated computer vision algorithm to allow picking of very diverse and complex objects randomly available on a belt or in bins. The algorithm exploits state-of-the-art feature descriptors for an approach that is robust against occlusions and distracting objects, and invariant to scale, rotation or illumination changes. Finally, the performance of the designed picking workstation is tested in a large experimentation focused on the management of pharmaceutical items.

Keywords: centralised distribution centre, automated picking workstation, pharmaceuticals, object segmentation, computer vision

1 Introduction

International healthcare systems are under increasing pressure to reduce waste and eliminate unnecessary costs while still improving the quality of patient care. Healthcare logistics and supply chain management are therefore coming under a great deal of scrutiny from both practitioners and academics (Bradley 2000, Battini et al. 2009).

For example, Bowman (1997) cites that healthcare supply chain inefficiencies amount to $11 billion (or 48%) of the total annual cost of $23 billion. Among those processes with potential for improvement, pharmaceutical logistics is significant in terms of the resources and costs involved and their effect on the final perceived service level (de Vries 2011).

Traditional management is therefore currently under scrutiny and innovative models are being implemented on a continuous basis. For example, some contributions have recently appeared which describe methodologies and the effects of the introduction of centralised drugs management on order issue and receipt, centralised warehouse management, distribution to end users or simply regarding centralised logistics management. In this context it is clear that the new emerging figure of central distributor is appreciated for the benefits it brings when introduced into the supply chain, both when managing ward stocks (hence the reference to a Ward Stock Drug Distribution System - WSDDS) and when dispensing unit dose (hence the reference to a Unit Dose Drug Dispensing System - UDDDS) (Summerfield 1983).

The process of picking items is critical to the performance of distribution centres. This paper therefore focuses on an automated pick-and-place workstation whose operative behaviour is based on innovative computer-vision-driven robotics (as defined in Asadi 2011) and whose main potentialities are described below:

- *Different object types and a highly variable appearance*: pharmaceuticals are characterised by highly variable appearance in terms of colour, size, primary packages (i.e. regular-shaped boxes, irregular-shaped boxes with transparents, flowpacks, etc.). The workstation manages different types of object of different dimensions and complexity, available for both WSDDS and UDDDS;
- *Randomly available objects*: most of the picking systems consider the scenario of well-separated objects, well-aligned on the belt and with synchronised grasping of the objects. Pharmaceuticals are sometimes characterised by irregular dispositions in a bin or on a conveyor belt, especially when items in flowpacks are handled or UDDDSs are served;
- *Multiple instances and distractors*: while in other image processing and computer vision applications the basic objective is to identify the single best instance of the target/query object, with pick-and-place applications the aim is not just to classify the first (or best) instance but to determine the locations, orientations and sizes of all or most of the duplicates/instances. Object duplicates can have different sizes, poses and orientations, and can be seen from different viewpoints and under different illumination. Moreover, in real-life applications the system must also account for the presence of distractors, i.e. other types of objects that differ from the target object and which should not be detected;
- *Heavily occluded objects*: as a consequence of the latter requirements, objects can be severely occluded;
- *High working speed*: when picking workstations are included in fully automated UDCs, the required working speed is very high; a fast detection technique is used to process up to a hundred objects a minute.

The automated picking workstation described in this paper uses state-of-the-art computer vision techniques based on local features, specifically single-point SIFT (Lowe 2004), which have proven to be robust to scale and translation variations, rotations and, at least partially, illumination changes. When handling complex, reflective, low-textured and heavily occluded objects, humans also rely only on very few visual features. To obtain multiple object identification in such complex scenarios we use a novel clustering method which exploits the Euclidean transformation hypothesis and the definition of a small set of *principal points* of the shape, i.e. points that characterize and delimit the object shape. To improve accuracy with low-textured, reflective or semi-transparent objects, multiple models of the target object can be used.

This paper is structured as follows. Section 2 analyses related publications. Section 3 describes the main components and characteristics of the proposed workstation. In section 4, a wide experimentation in the field of localisation and picking of pharmaceuticals is conducted and the results reported and commented. Finally, section 5 outlines some conclusions.

2 Literature review

As anticipated in the introductory section, this paper focuses on the characteristics and effects of the adoption of an automated picking workstation in a pharmaceutical centralised warehouse, using vision-based algorithms for object detection. The literature review is therefore performed by analysing related issues: healthcare supply chains (section 2.1), picking systems and workstations (section 2.2), vision-based systems for pick-and-place applications with particular emphasis on the types of object handled and their characteristics (section 2.3).

2.1 Healthcare supply chains

The healthcare supply chains can be conceptualised as comprising five main actors (Burns et al. 2002): (a) *healthcare producers*: manufacturing and service companies including pharmaceutical and biotechnology manufacturers, medical device makers, medical suppliers and information technology firms; (b) *healthcare product intermediaries*: wholesalers, mail order distributors and group purchasing organisations; (c) *healthcare providers*: hospitals, physicians, integrated delivery networks and pharmacies; (d) *healthcare fiscal intermediaries*: insurers, health maintenance organisations and pharmacy benefit managers; (e) *purchasers*: government, employers, individuals and employer coalitions.

The portion of the supply chain on which this paper focuses is the relationship between pharmaceutical companies and hospitals and clinics.

Such a relation is also analysed in Battini et al. (2009) where, in the case of companies supplying pharmaceuticals, the authors state that 3 main management models are implemented:

1) A traditional approach in which there is a central pharmacy store in every hospital that decides what and how to buy. This is the most widespread system (Dongsoo 2005);

2) Centralised management of drugs in a district or regional centre (Unique Distributive Centre - UDC), whose insertion in the supply chain is mainly justified by e.g. expected savings due to elimination of stocks duplication along with economies of scale in the purchasing, storing, handling and transportation of items (Nollet and Bealieu 2003, Nicholson 2004, Chandra 2008);

3) All physical managing and pharmaceutical movements are carried out by a third party (logistics operator). However, the hospital pharmacy is in charge of deciding what and how to order.

These models are schematised in figure 1 using the framework introduced in Caldeira Pedroso and Nakano (2009).

[TAKE IN FIGURE 1]

This paper focuses on innovative healthcare supply chains shaped as described in model 2, and in particular on an automated picking solution to improve their performance.

2.2 Picking systems and workstations in distribution centres and warehouses included in healthcare supply chains

Order picking and the process of retrieving products from storage or buffer areas in response to a specific customer request are among the most labour-intensive operations in manual systems and are a very capital-intensive operation in automated systems (Goetschalckx and Ashayery 1989, van den Berg and Zijm 1999, Tompkins et al. 2003).

The focus of this paper is therefore on innovative solutions for improving the behaviour of picking techniques in healthcare supply chains.

Order picking systems can be classified according to whether humans or automated machines are used (de Koster et al. 2007). The former group includes picker-to-parts, parts-to-picker and put systems. Picker-to-parts systems are characterised by pickers who walk or drive along the aisles to pick items. Parts-to-picker systems include Automated Storage and Retrieval Systems (AS/RS). These use mainly aisle-bound cranes that retrieve one or more unit loads (pallets or bins) and bring them to a pick position from where the picker takes the required number of pieces. Next, the remaining load is stored again. Put systems consist of a retrieval and distribution process where items are initially retrieved, either in a parts-to-picker or in a picker-to-parts manner. Afterwards, a bin with these pre-picked units is usually offered to an order picker who distributes them over customer orders.

Alternatively, automated picking (e.g. see Figure 2) and picking robot systems use machines for order picking and are preferred for the picking of small, valuable, and delicate items.

Most warehouses typically feature a mixture of such models, examples of which in the field of healthcare supply chains are reported in Figures 3, 4 and 5 which illustrate combinations of automated picking with manual picker-to-parts, manual parts-to-picker or robotic picker respectively.

[TAKE IN FIGURES 2, 3, 4, 5]

This paper focuses on the robotic picking workstation, which is particularly suitable for applications similar to those depicted in Figure 5.

2.3 Items managed by pick-and-place robots using vision-based detecting algorithms

The scientific literature on vision-based pick-and-place (or object grasping) is very abundant. Table 1 summarises some significant existing approaches by focusing on vision-based object grasping systems. Table 1 also emphasises which objects are considered in those papers and whether the characteristics listed in Section 1 are considered (YES), not considered (NO) or not explicitly stated (U). In particular, the experimental conditions (whether distractors, multiple instances of the same object or occlusions are accounted for, whether random disposal of objects is considered, whether illumination is controlled or not) and the characteristics of the objects (whether or not objects of different sizes, transparent or reflective are considered) are reported for each paper and for the workstation presented in the work.

Some of the published papers deserve additional discussion. For example the pioneering work of Sanz et al. (1998) exploits image processing techniques to determine the grasping points for picking up unknown everyday objects. Similarly, Saxena et al. (2008) do not concentrate on objects themselves but on identifying their grasping point. Indeed they are concerned with grasping all the available objects rather than looking for a specific object. Synthetic models of typical objects with manually selected grasp areas (neck for glasses, handle for cups, etc.) are indicated and used to train the system. However both these approaches consider isolated objects with few or no distractors and no severe occlusions (at least not of the grasping point).

Unfortunately, the cluttered appearance of objects due to occlusions and distractors tends to make these approaches unreliable in real-life scenarios. By contrast, Rahardja and Kosaka (1996) perform bin-picking of industrial objects using stereo vision. Simple visual global features such as region area, eccentricity, and gray scale mean value are adopted for object recognition and pose estimation. However, Rahardja and Kosaka (1996) do not cover the crucial aspect of transparencies which are commonplace when managing healthcare market items.

Some solutions exploit additional sensor modalities to improve the system performance. For instance, Mohan et al. (2011) propose the combined used of a structured light for computing a 3D reconstruction of the scene using a standard single camera, while Prasse et al. (2011) merge computer vision and camera with RFID processing, which guarantees a more accurate identification of the objects. Both these solutions, however, bring additional costs, more computational burden and are not applicable to all the conditions (for instance, structured light can be severely misled by uncontrolled natural light).

The picking workstation described in this paper therefore aims to satisfy requirements coming from a market field that is continuously investing in IT solutions (Gunasekaran et al. 2006) in order to overcome traditional approaches and obtain improvements. It disregards published experimentation with vision-based object-grasping approaches.

[TAKE IN TABLE 1]

3 Characteristics and components of the picking workstation

Our proposed workstation is specifically oriented to a typical pick-and-place system, examples of which in the healthcare market field have been described above. Further details are reported in the sequel and depicted in Figure 6.

[TAKE IN FIGURE 6]

The objects are either dropped in bulk onto bins positioned on a belt or randomly dropped directly onto the belt. The belt is moved to bring the object to the picking station where two cameras acquire a pair of synchronised stereo images. The first camera is used to segment the image in order to detect the target objects, their 2D position and their orientation. The second camera is used to estimate the distance from the cameras of the object to be picked up. It does so by composing, together with the first camera, a classical stereo pair: this estimation, through a proper calibration of the whole system, will allow the correct 3D localisation of the object. These 3D coordinates ((x; y) obtained from the segmented image and z from the stereo-based 3D estimation) and the object's main orientation are sent to the robot which picks up the selected object and places it in the placing station. This architecture is fairly standard in pick-and-place robotic applications where objects normally enter the system in an ordered manner on a line, making the computer vision process easier. The novelty of our proposal is that the robustness of the method and its generality mean that unordered objects also become tractable. This characteristic is particularly interesting in the field of pharmaceuticals where, as mentioned above, flow packs, irregularly-shaped packaging, and UDDDS are encountered.

The main procedure of the system iterates through four main phases. In the *Object Detection* phase, the objects in the current image are detected and localised (in 2D). This is the core of the system and is described in more detail below. Once the objects are detected, one of them is selected as the next one to be picked up. This *Object Selection* phase can be based on some models in order to optimize the robot trajectories, reduce the overall working time, and improve predefined objectives set by the customer. In our prototype, *Object Selection* is obtained by ordering the objects with decreasing distance from the robot (to account for the closest object first).

The third phase (*3D Object Localization*) exploits camera calibration to obtain 3D world coordinates of the grasping points of the selected object. Finally, these coordinates are sent to the robot which picks up the selected object (*Object Picking* phase).

This process is iterated by acquiring a new image from a single camera. The image segmented at the previous iteration could in principle be used to obtain the next selected object (without performing object detection again), but the picking of the object often shuffles the remaining objects.

A detailed flowchart of the Object Detection phase is shown in Figure 7. The left side of the flowchart shows the offline model acquisition. In fact the target object is modelled using multiple 2D models, both from the same view of the object and from different views/faces of the object. All the models are taken under free environmental illumination and using different object orientations in order to be robust to the reflexes created by a possible transparent container. M_j^i represents the *j*-

th model for the face *i* (the total number of faces is indicated by *F*), while is the set of principal points for the *j*-th model of the face *i*.

The right side of Figure 7 shows the online process which consists of two main phases: *Feature extraction and matching*, and *Object localisation*.

In “Feature extraction and matching”, significant features are extracted from both the object model and the current image. Among the possible local features to be used for model-image matching, we selected the SIFT features and the 2NN (two nearest neighbours) heuristic proposed in Lowe (2004). SIFT has proved to be very robust to noise and invariant to scaling, rotation, translation and, to some extent, illumination changes. Given the two sets of features (for the *j*-th model of face *i* and *K* from the current image – see Figure 7) the standard 2NN matching algorithm computes the Euclidean distance to find the image-to-model matches (or correspondences) , where each match contains the (x; y) coordinates on the two reference systems and the main orientation on the current image.

[TAKE IN FIGURE 7]

The “object localisation” step computes a registration transform between the model and the best location of the detected object in the current image. This is achieved by first clustering the matches using a voting scheme which allows us to estimate the object centre’s position (considering pure roto-translational, i.e. Euclidean, transform). Next, the Mean Shift algorithm (Fukunaga et al. 1975) is applied to account for uncertainty and inaccuracies (only the centres with a minimum number of contributing matches are considered correct). Finally, for each cluster the positions of a fixed number of principal points are computed in order to define the object delimiting shape and/or the grasping points.

In the example shown in figure 8, the numbers in black represent the estimates of the object's centre, the black cross the estimated centre position, while small circles in blue, red, yellow and green represent the estimates of the other four principal points.

More details concerning the algorithm implemented are available in Piccinini et al. (2010).

[TAKE IN FIGURE 8]

4 Experimental results

To validate our approach in the context of healthcare applications, experiments are performed on very different types of pharmaceutical/cosmetic objects. A summary of the objects used in these tests is given in table 2. For each object, a list of peculiarities is defined. Some peculiarities, such as texture or size, may aid detection, i.e. they are "positive" in the table. Others, such as reflectivity or transparency, may hinder it and are therefore denoted by "negative". The grade (from "Very Low" to "Very High") reported for each peculiarity indicates how much it applies to that type of object. The "Difficulty" column is a subjective evaluation of how difficult it is to detect the object. Figure 9 also shows some snapshots of the objects.

[TAKE IN TABLE 2]

[TAKE IN FIGURE 9]

The accuracy of our approach can be measured using different metrics:

- The *precision* at object level that accounts for the fraction (as a percentage) of detected objects that are correct;
- The *recall* at object level that accounts for the fraction (as a percentage) of existing correct objects that are detected (Makhoul et al. 1999);

- The *accuracy of the centre location*, more application-oriented. In a pick-and-place application the accuracy in determining the grasping point (e.g. the centre) is crucial, hence the distance between the detected coordinates and the actual ones is computed and expressed both in pixel ( ) and as a percentage ( ), as described in equation (1):

(1)

where is the mean area of the analysed items, expressed in pixels and strictly connected with the zoom defined on the camera. In the analysed case study, values registered for are reported in the sequel:

[TAKE IN TABLE 3]

- The fact that at least one catchable object is detected at each iteration (in order to "feed" the robot) and consequently the picking of all the objects after a certain number of iterations (equal to the number of items in the order or all the available items in the bin or on the conveyor belt; specifically, in our experimentation the picking of all the available items is studied). An example of such behaviour is shown in figure 10. Given all the items randomly distributed on the conveyor belt or into the bin, our approach localises products that are highlighted by green boundaries. The yellow-bounded item is the one selected in accordance with predefined picking and placing algorithms and objectives, which is then positioned in the placing station. In the following iteration, a new detection of items occurs and a new selection of the product to be placed in the placing station is executed. The process continues until no more items are available on the conveyor belt or in the bin or until no more objects are detected. In the former case, the picking sequence is correctly executed, with a performance rate of 100%. In the latter case, inferior performance is registered. Specifically, the more undetected objects are registered, the less efficient the localising process is.

[TAKE IN FIGURE 10]

The precision, recall and accuracy of the centre location are based on fundamental truths obtained by subjective operator evaluations.

Last but not least and importantly for our purposes: we also aim to evaluate the efficiency of our proposal by measuring the computational and operational time.

The experiments are carried out using three different scenarios: the first includes a rather simple situation with few objects (even if randomly available which produces occlusions) and no distractors (“EASY”); the second scenario considers a more complex situation with tens of objects (“COMPLEX”); the third scenario (“DISTRACTORS”) is a complex case which also includes distractors (paper, cellophane or scotch tape).

Each experiment is run three times with a new image and new objects and then averaged.

Results obtained are reported in table 4 and in figures 11 and 12, where the aforementioned data is also depicted in order to increase its readability.

[TAKE IN TABLE 4]

[TAKE IN FIGURE 11]

[TAKE IN FIGURE 12]

It is worth noting that the general accuracy is similar to that obtained in previous experiments with different objects (Piccinini et al. 2010). The performance degrades when more challenging objects are considered such as pills which are untextured and bright and which make visual detection harder. Uncommon behaviour can be identified in the case of “Band-aid Box” objects. These are simple objects for which however recall is limited because they are thicker and tend to overlap each other with out-of-the-plane rotations. This violates the assumption of pure Euclidean transformation hypothesis mentioned in the introduction. In addition, the better performance achieved in some cases for small pills compared to large ones can be ascribed to the lower probability of occlusions in the case of small objects. Finally, the consistent improvement in centre accuracy in the “Distractors” scenario for “Toothbrush Head” objects is also due to the improvement in precision at object level. This can be explained by the highly textured nature of this object and thus to its robustness to occlusions caused by distractors.

Given that our target scenario is the use of the proposed workstation in health care systems, the values obtained for the execution of both isolated and sequenced detection, picking and placing actions, performed in a complex environment, will allow comparison between the introduction of an automated workstation in substitution with a manually-managed picking area.

The benefits associated with the insertion of robotics in healthcare systems have been studied since the 1980s (Minifie 1989). Traditional manual picking systems (similar to those described in figure 3) have been widely studied in the past (Hwang and Cho 2006, Pan and Shih 2008, Rim and Park 2008). Nevertheless, congestion often occurs. When product characteristics are suitable, i.e. small items with no particular stocking or handling conditions, the systems described in figure 5 are therefore implemented. A recent contribution has studied the problem of subdividing picking work in different workstations (Hou et al. 2009).

In our experimentation, operative environments depicted in figures 4 and 5 are compared in terms of detection, picking and placing execution time per cycle. Subsequently, sequences of detection, picking and placing actions are studied. Finally, an economical analysis is traced.

In the robotic picking workstation, mean registered time per cycle for image acquisition, image elaboration, picking and placing are described in table 5. Next, the handled items per minute are computed.

[TAKE IN TABLE 5]

Otherwise, in the case of a manual workstation, such times are estimated by MINIMOST System (Zandin 2003), available for measuring work in case of identical cycles, typically of short duration. Specifically, the General Move Sequence Model is implemented and the studied work is analysed by the following sequence of parameters:

- A (Action distance). This parameter covers all spatial movements or actions of fingers, hand and/or feet, either loaded or unloaded by an object;
- B (Body motion). This parameter is used to specify vertical motion of the body, including the exercise of eye travel;
- G (Grain control). This parameter covers all manual motions (mainly of the fingers, hand or foot) employed to obtain complete control of an object, before moving it to another location;
- P (Placement). This parameter is used to analyze actions at the final stage of displacement.

Such parameters are structures in the sequence ABGABPA, whose parts are grouped in sets similar to those executed by the robot:

- Object detection (AB)
- Grasping (G)
- Placing (ABPA).

Next, parameter indexing is evaluated. By observing or visualising the operator's actions during each phase of the activity, a duration (reported in the subscript of each parameter) is evaluated by matching each parameter variant with the data card reported in Zandin (2003). For example, the variant is associated with any displacement of the fingers and/or hands at a distance greater than 10 cm and less than or equal to 20 cm.

The full evaluated sequence per studied object is reported in the second column of table 6.

Subsequently, the total operative time per cycle is computed and expressed both in TMU (Time Measurement Unit; 1 TMU=0.036 seconds) and in seconds. Finally, the last column describes the effects of the implementation of a manual workstation, in comparison with a robotic one. A reduction in the handled items per minute is registered in the range [-70.27%, -196.97%].

[TAKE IN TABLE 6]

Hence the introduction of the robotic workstation induces the possibility of executing more picking cycles per minute in the range of [+41.27%, +66.33%] (see table 5, last column).

As mentioned above, the behaviour of the system during sequences of detection, picking and placing actions is finally studied. Results obtained are depicted in figure 14. Whilst dropper, glass syringe, toothbrush head, hand gel and band-aid box demonstrate the complete correct execution of the sequence (to which 100% of performance is coupled), syringe and pills (initially classified as critical items) demonstrate a lower performance.

[TAKE IN FIGURE 14]

Nevertheless, the good margins mentioned above for detection, picking and placing time per cycle address guidelines for improving the behaviour of the workstation, which can be loaded with items in bins and equipped with a shaker, moving the working desk slightly. When a bin containing products is located on the working desk and no object is detected by the robot, a shake could take place in order to change objects disposition and re-apply the object detection algorithm. In such cases, given the aforementioned robot operative cycle (image acquisition, image processing, picking, placing), the two previous steps are executed as many times as required but picking and placing are executed only once. Table 7 describes the cycle of a robot where, in the case of critical items (syringe and pills), even if image acquisition and processing are executed twice, the improvements in terms of handled items per minute, in comparison with a manual workstation, still remain at 41.27% for syringe and at 60.24% for pills (first two columns of table 7). Furthermore, improvements are still assured if repetitions are executed up to 4 times (see table 7).

However, experimental results reported in figure 14 demonstrate that less than one shake per object detection is enough to ensure the complete execution of the picking sequence.

Such a result is crucial for a picking area where the insertion of automation induces a consistent improvement in performance, regarding both the speed of action execution and the registered reliability. Alternatively, picking errors in the range are registered when manual picking areas are analysed (Osualdella 2011).

Furthermore, whilst the human errors are characterised by undetectability and are often registered by the user, the errors made by the proposed automated system are managed by an internal control system, before reaching the user. Specifically, in the manual picking system depicted in figure 4, the operators could include in the customers orders wrong medicines, or correct objects but with an incorrect amount, and no traceability of their actions is available (Abbasi 2011). So, only the final user can detect errors and complain with the warehouse managers. On the contrary, in the picking automated system presented in this work the occurring errors are related only with the presence of an object in the bin, that, however, is not detected. Such errors are automatically managed by repeating the image acquisition and processing steps in a re-called bin containing the same medicines. Obviously, picking and placing steps occur only once, when a correct object detection occurs.

In tables 8 and 9 the objects managed per minute, respectively in the manual and in the robotic system when errors are taken into account, are reported. Specifically, in the computation of correct cycles per minute executed in a manual picking system, the errors percentage reported in aforementioned (Osualdella 2011) are considered and used for correcting values presented in column 8 of table 6. Alternatively, in the computation of the correct cycles per minute executed in the robotic picking system, the errors percentages emerging in the execution of a picking sequence (depicted in figure 14) are used for evaluating how many times image acquisition and processing steps need to be repeated.

The introduction of the robotic workstation induces again the possibility of executing more picking cycles per minute in the range of [+42.86%, +65.59%] (see table 9, last column).

[TAKE IN TABLES 8 AND 9]

Finally, an economical analysis of the behaviour of the manual and the robotic picking system, respectively, is carried out. Specifically, as shown in figures 4 and 5, both systems are constituted by an A-frame module, an automated parts-to-picker module, a conveyor belt, with groups of pharmaceuticals, created by the A-frame module and final containers for satisfying customers orders. Moreover, whilst pickers serve the manual system, the robotic workstation serves the automated system. Hence, by focusing only on the differential costs (hourly manpower in the first case and hourly cost of the robotic workstation in the latter), unitary costs for handling each item picked from bins in the automated parts-to-picker module and placed on the conveyor belt are reported in tables 10 and 11. Specifically, both the ideal case without errors and the case with detection errors are analysed. In table 10 an operator hourly cost of 27 €/hour is compared with the case of a robotic workstation hourly cost in the range [40; 80] €/hour, related with differential equipments of the robot (i.e. dimension of the picking arm, available movements in the picking arm ...). The obtained results will address the choices of managers and engineers engaged in the analysis of conditions, by also assuring economical benefits from the insertion of the robotic workstation in the market. Specifically, the automated solution results to be cheaper if its characteristics and operative conditions assure to not overcome limit costs in the range [50, 80] €/hour, that are underlined with a bold character in table 11. Obviously, case specific alternative studies can be executed in different operative environments, i.e. by varying operators hourly costs and/or robotic workstation customized characteristics.

[TAKE IN TABLES 10 AND 11]

5 Conclusions

More and more research is being conducted on centralised distribution of pharmaceuticals in healthcare systems due to its effect on final costs perceived by users. Solutions addressing its efficiency are therefore subject to ongoing study.

This paper focuses on the picking process commonly found in centralised warehouses. Specifically it describes a new picking workstation available for insertion in automated pharmaceutical distribution centres and which is capable of replacing manual workstations and improving working time. A sophisticated algorithm is implemented which exploits state-of-the-art feature descriptors to allow picking of very diverse and complex objects randomly available on a belt or in bins, even where occlusions and distractors exist.

A wide experimentation is executed by focusing the performance analysis in the promising field of healthcare, often disregarded by computer vision researchers.

The values obtained for precision and recall suggest the use of the new studied workstation with scarcely detectable objects occurring in the healthcare field, often characterised by irregular shape and flowpacks, along with transparencies.

Next, a comparison with the studied automated workstation with a manual picking-managed zone is carried out. Improvements in the handled items per minute are registered in the range of [+41.27%, +66.33%]. Furthermore, interesting improvements still remain when, with very critical items such as pills, the image acquisition and processing step should require an iteration, e.g. following a shake. Up to 4 iterations can be assured per image without inducing inefficiencies in the system. However, in the executed experimentation less than one shake per object detection is enough to ensure the complete execution of the picking sequence.

Furthermore, the errors occurring during picking are deeply analysed, both in their content and in their effect on the system's technical and economical performance. Specifically, cycles per minute without and with the presence of picking errors are compared. The introduction of the robotic workstation induces again the possibility of executing more picking cycles per minute in the range of [+42.86%, +65.59%].

Finally, an economical analysis is carried out and unitary handling costs are computed for both the manual and the robotic system. Moreover, both the ideal case without picking errors and the case with detected errors are analysed by defining limit cost values addressing the choice of the proposed robotic workstation.

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Figure 1 Main frameworks describing the relation between pharmaceutical companies and hospitals and clinics

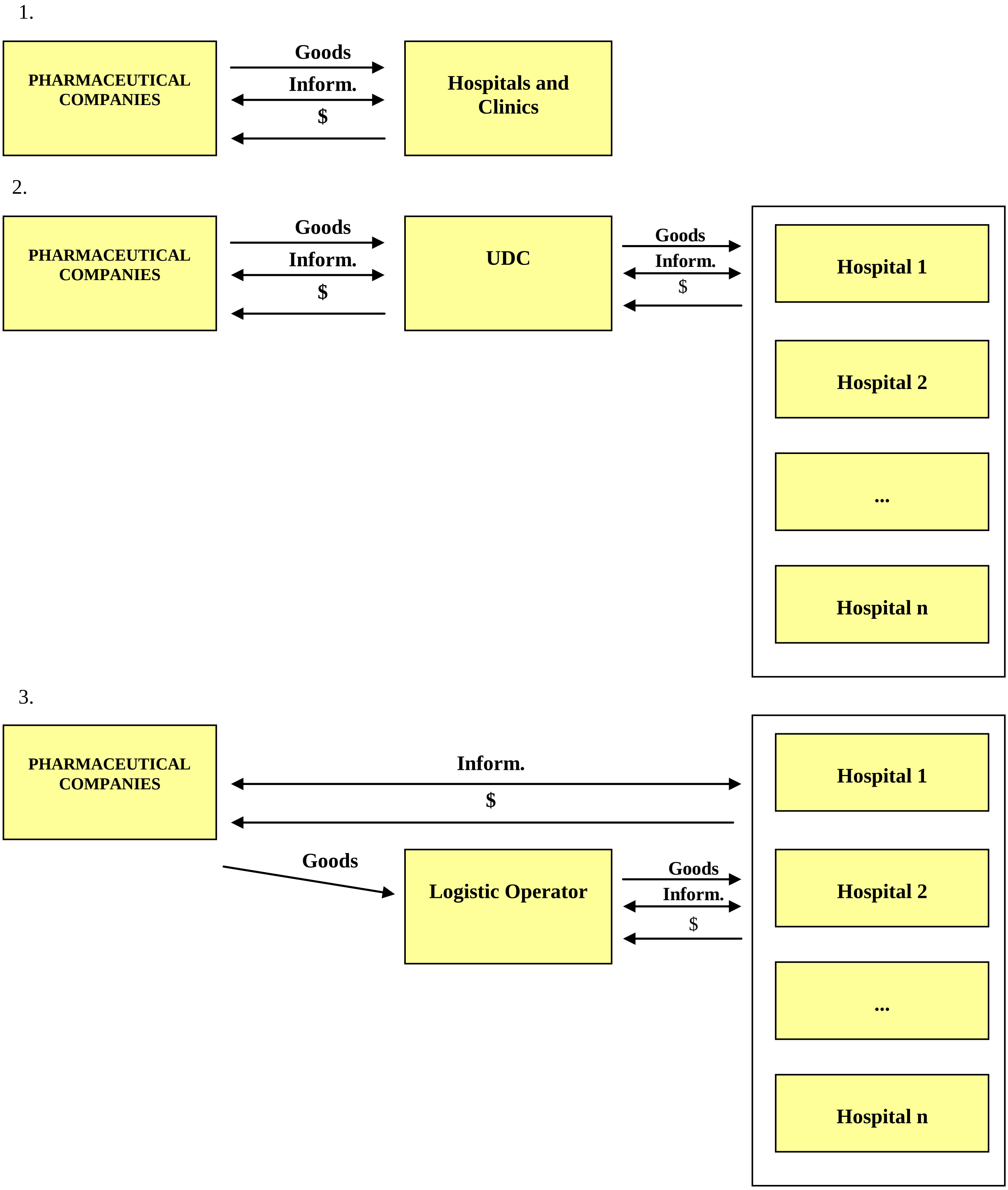


Figure 2	**An example of an automated picking system (named A-frame), widely used in pharmaceuticals distributions centers**

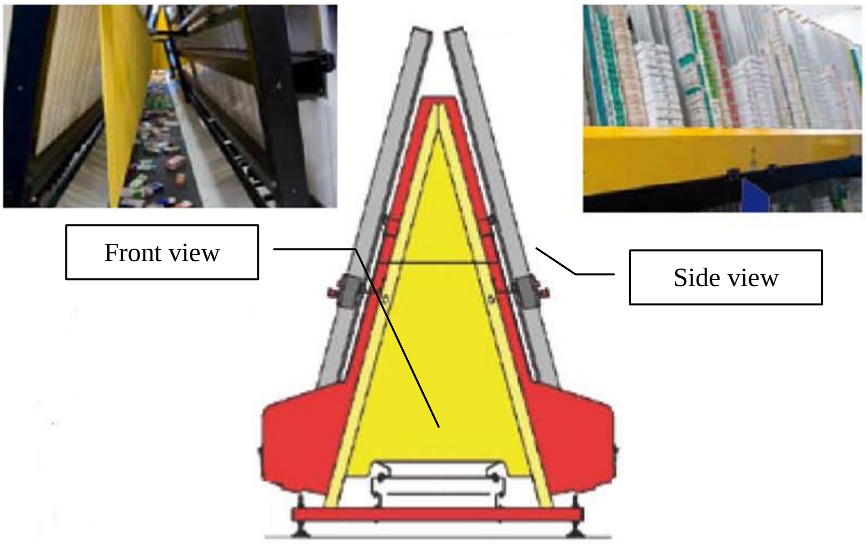


Figure 3 A warehouse scheme with a composition of automated picking and manual picker-to-parts system

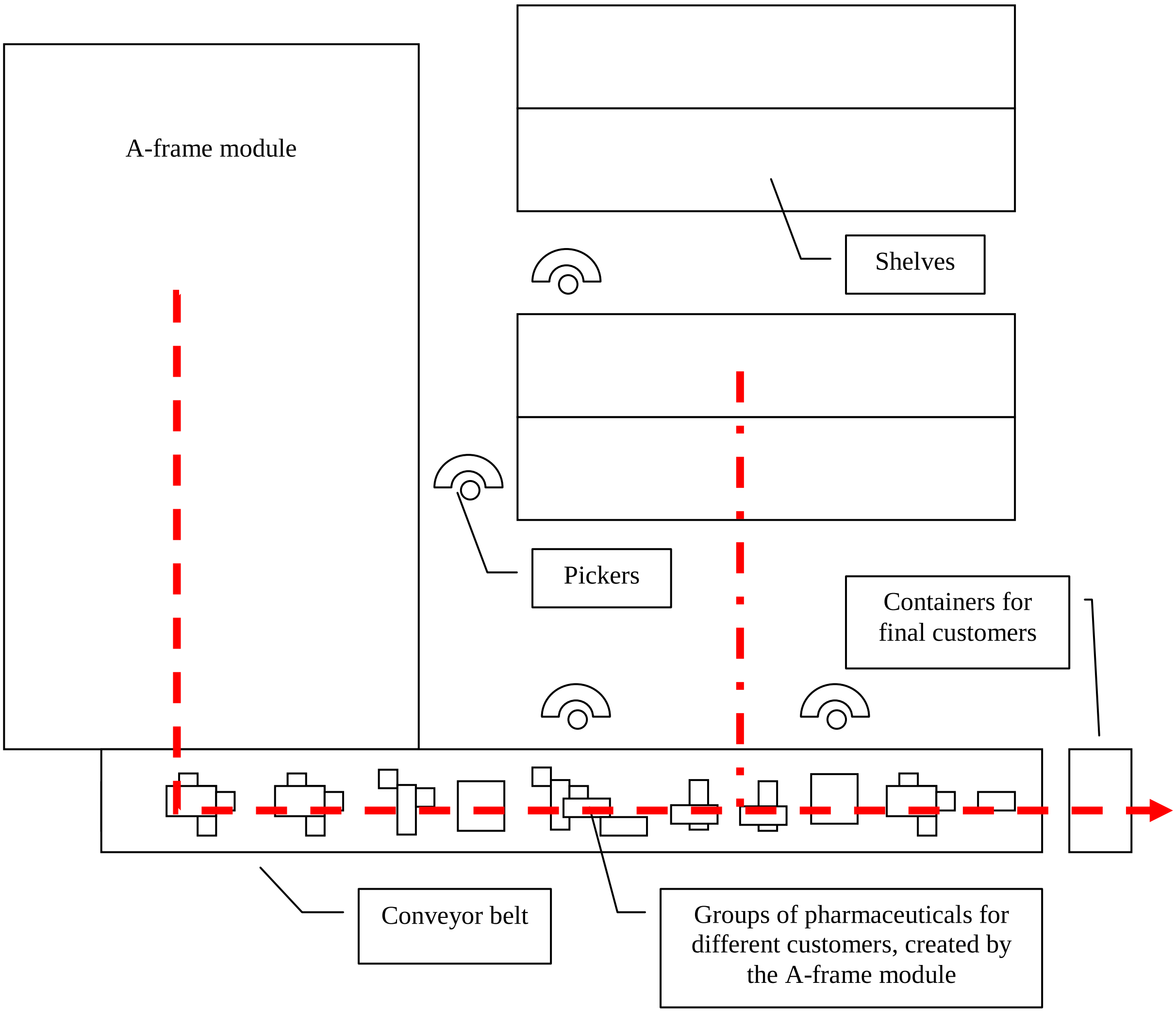


Figure 4 **A warehouse scheme with a composition of automated picking and manual parts-to-picker system**

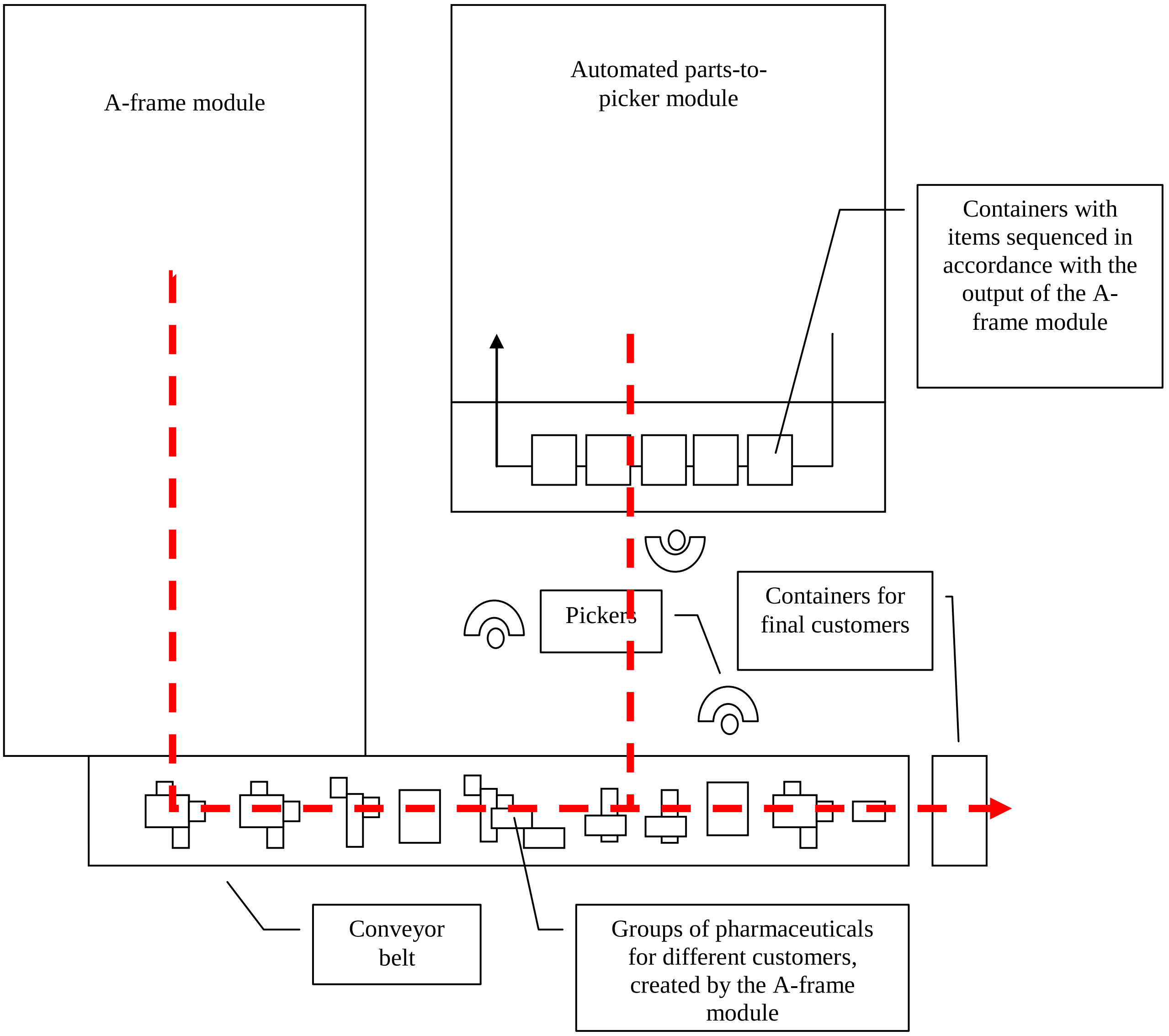


Figure 5 A warehouse scheme with a composition of automated picking and robotic parts-to-picker system

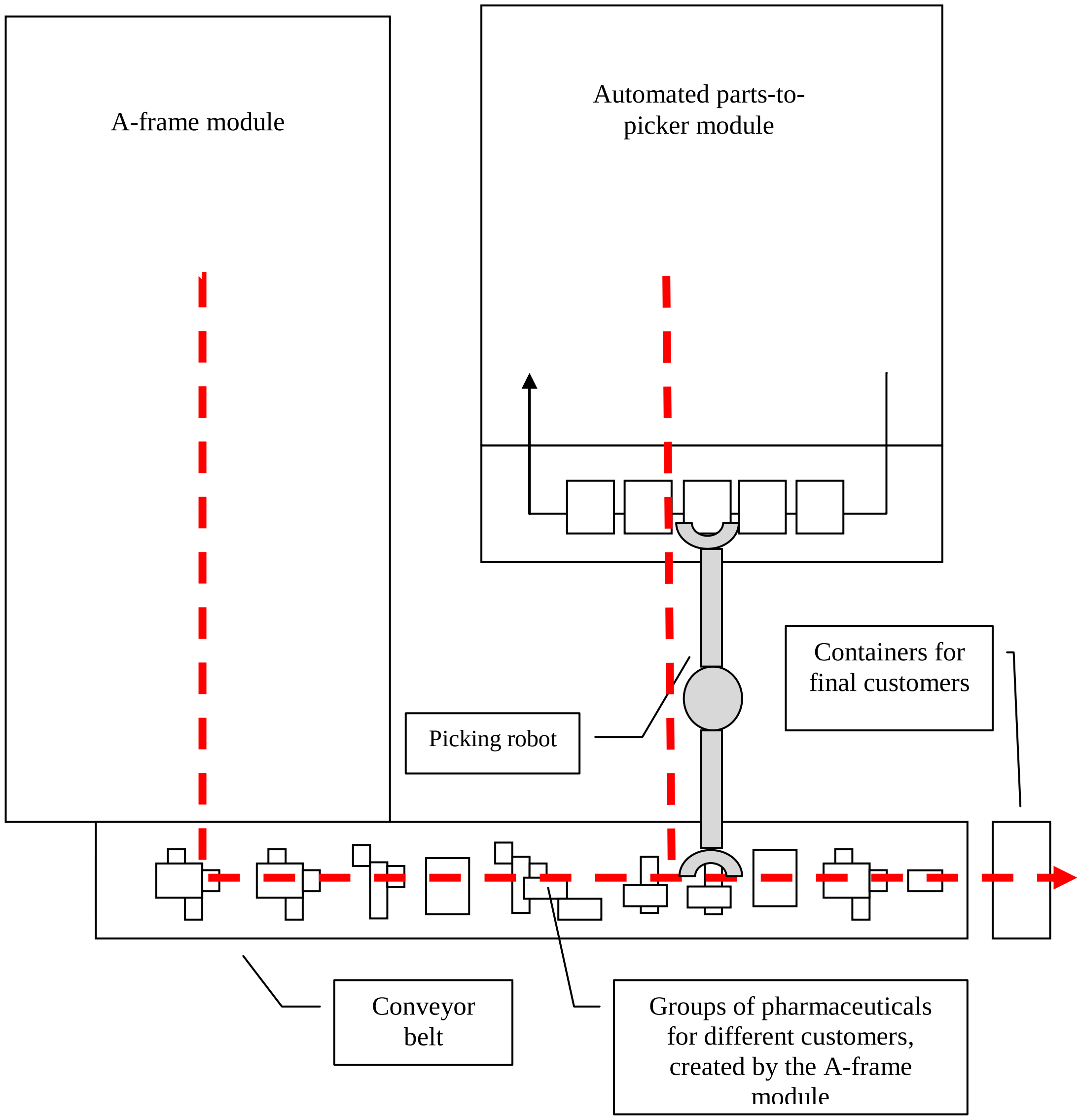


Figure 6 General overview of the workstation

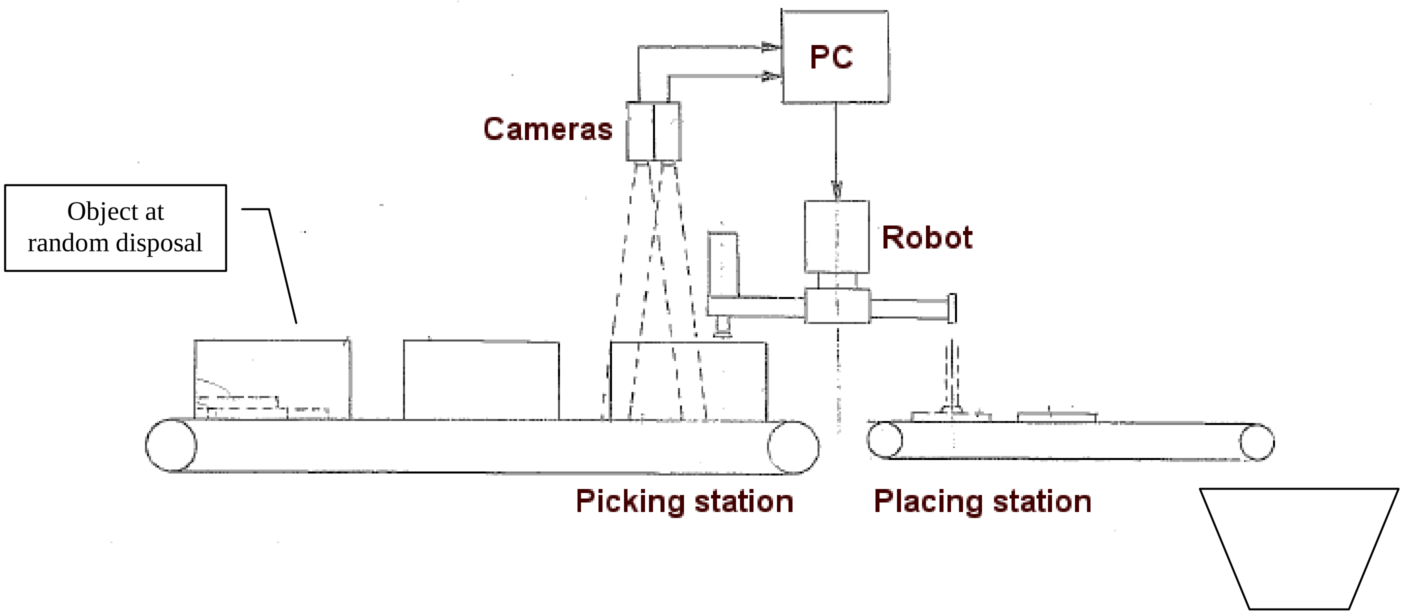


Figure 7 **Flowchart of the "Object Detection" phase**

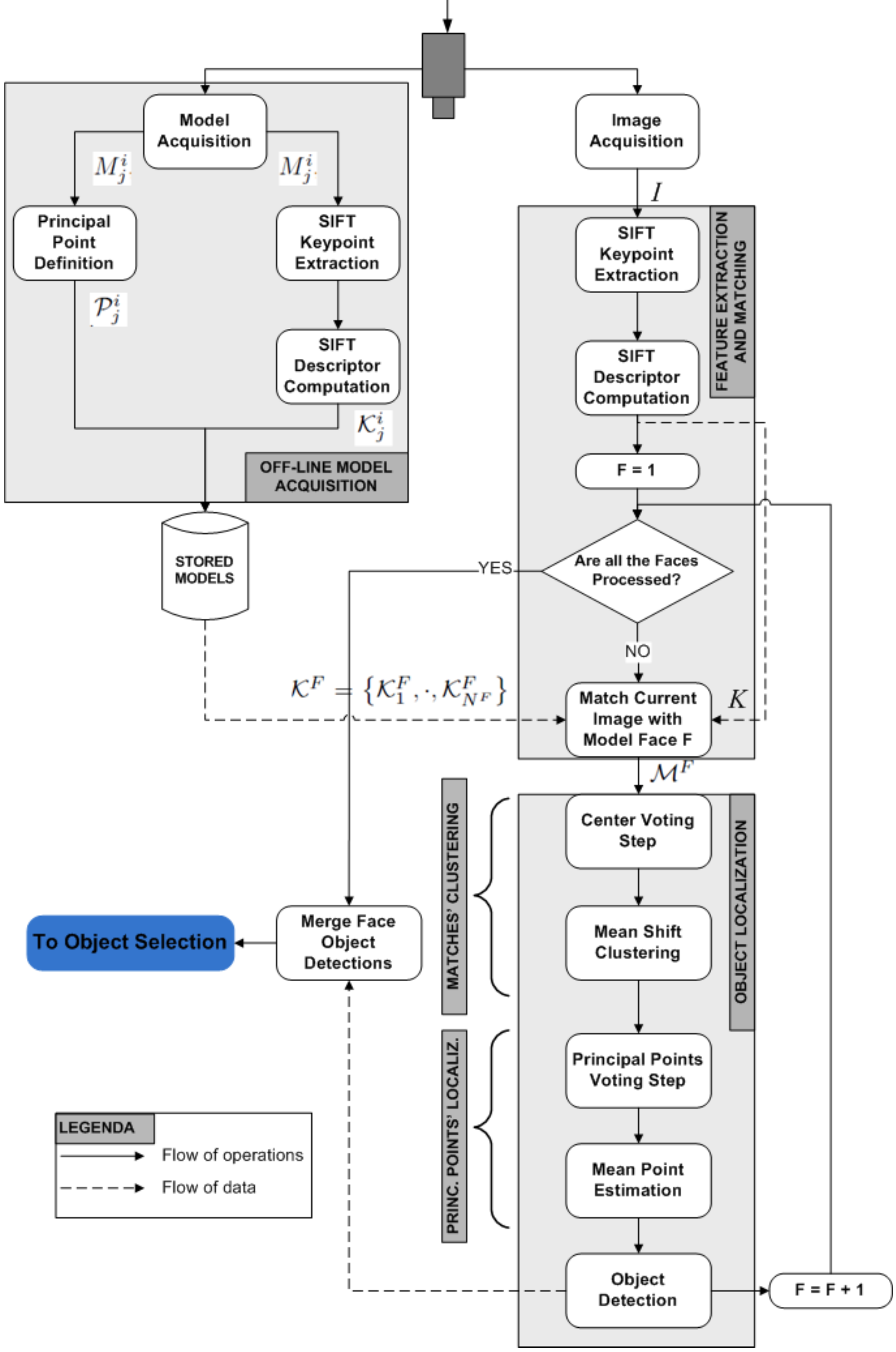


Figure 8 Examples of “Object Dectetion” results

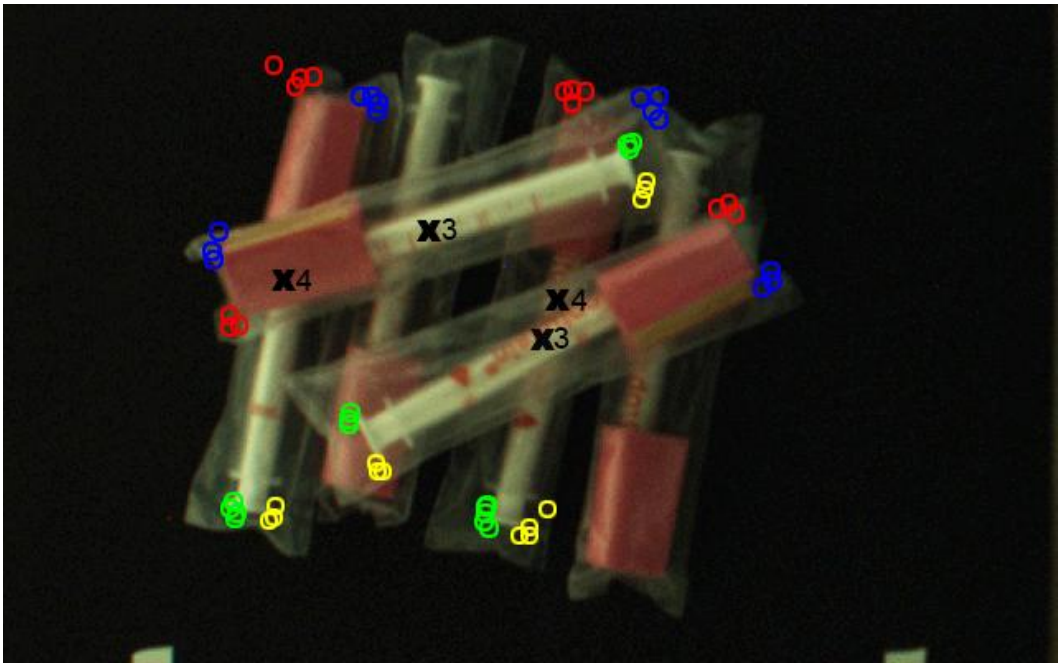
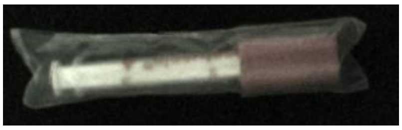
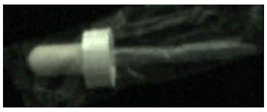


Figure 9 Exemplar images of the objects used in our tests



(a) Syringe



(b) Dropper

(c) Glass syringe

(d) Toothbrush head

(e) Hand gel

(f) Band-aid box

(g) Large pill

(h) Medium pill

(i) Small pill

Figure 10 An example of picking sequence for "Toothbrush heads" (yellow indicates the selected object)

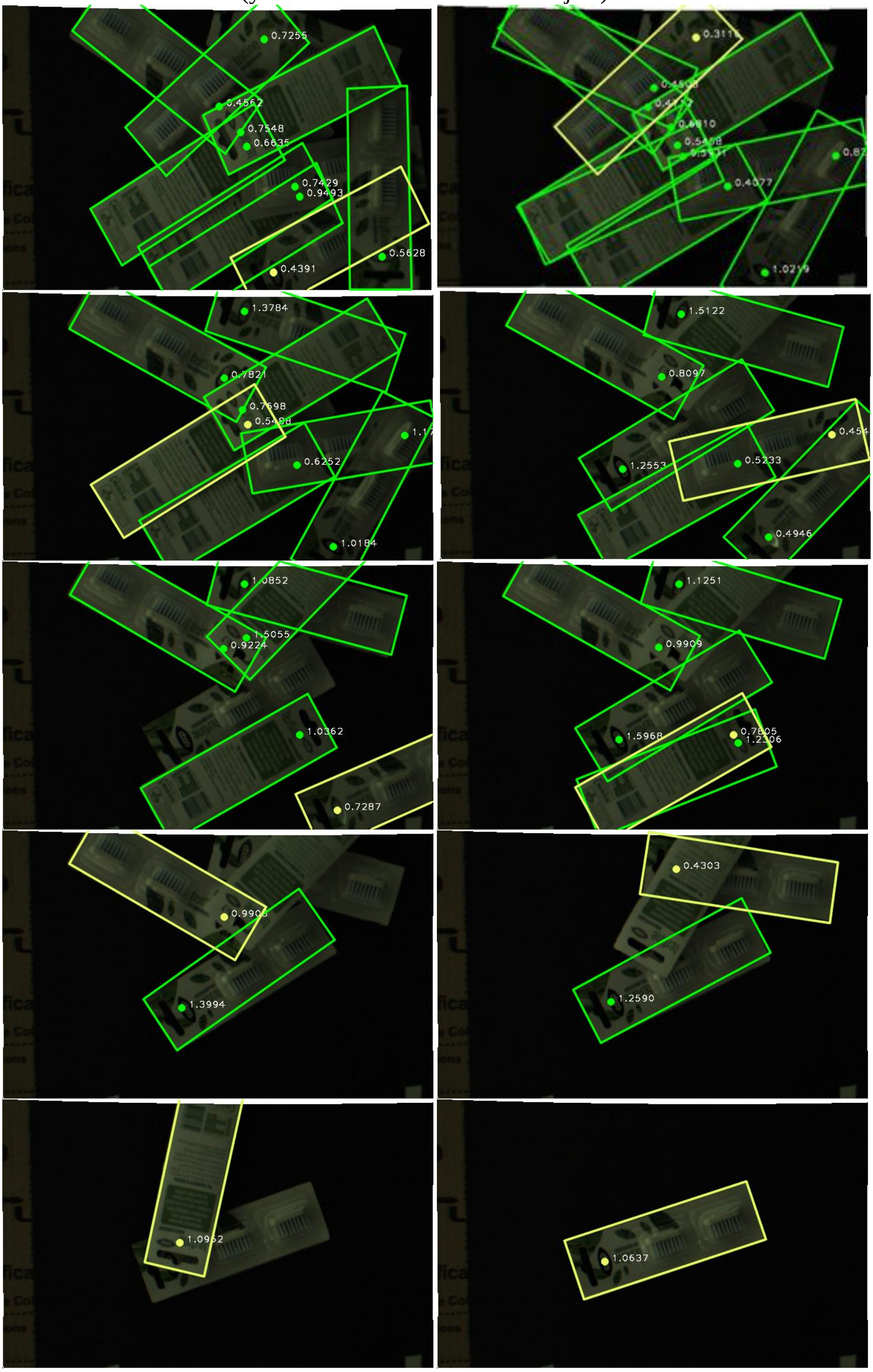
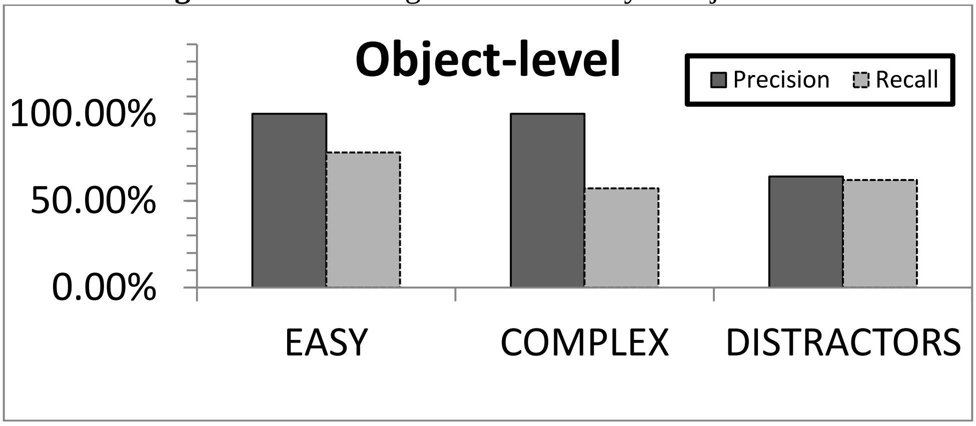
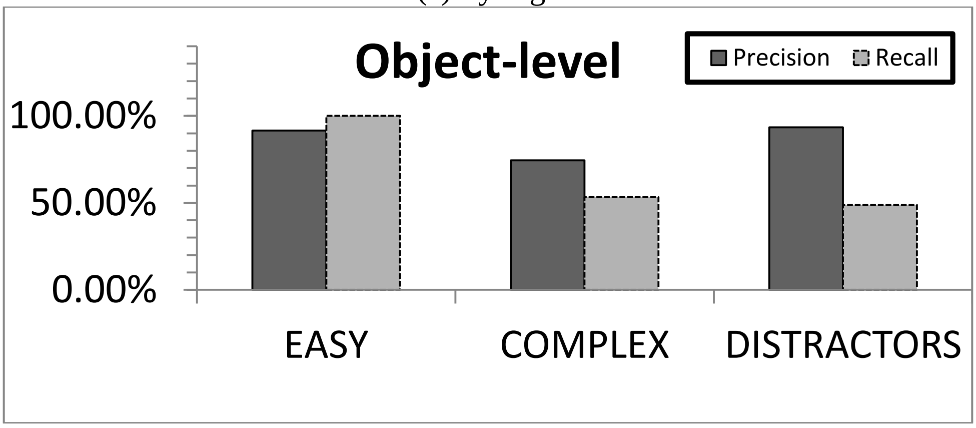


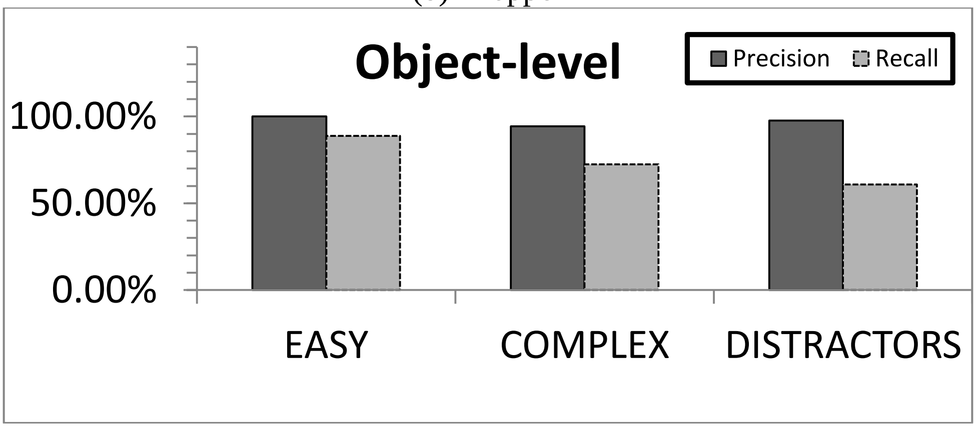
Figure 11 Histograms of accuracy at object-level



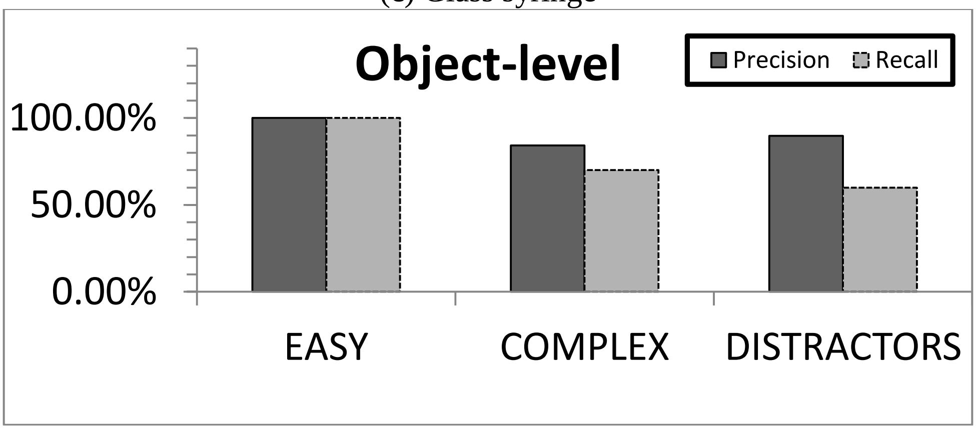
(a) Syringe



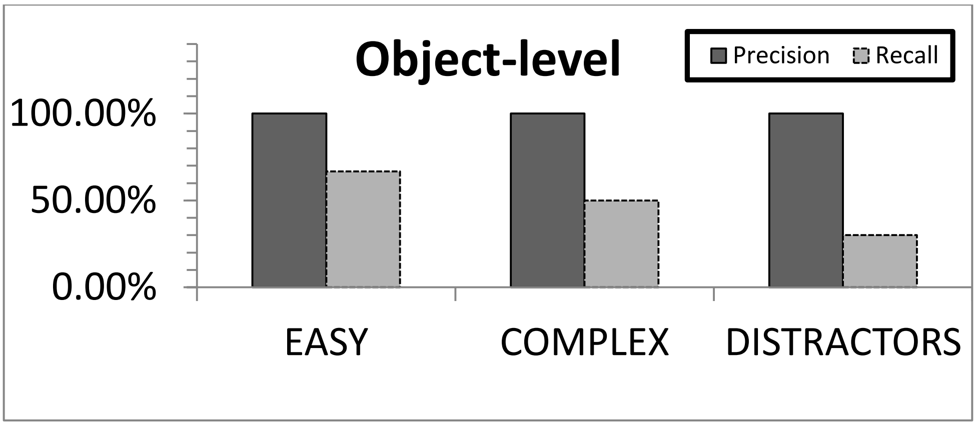
(b) Dropper



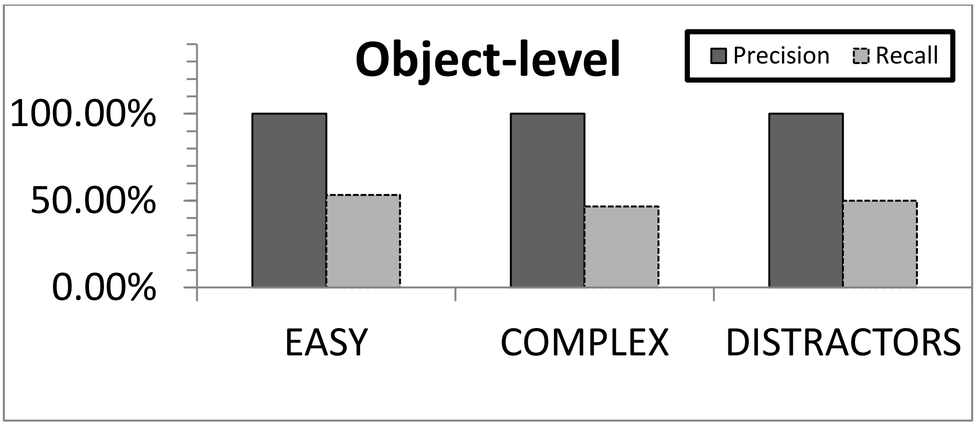
(c) Glass syringe



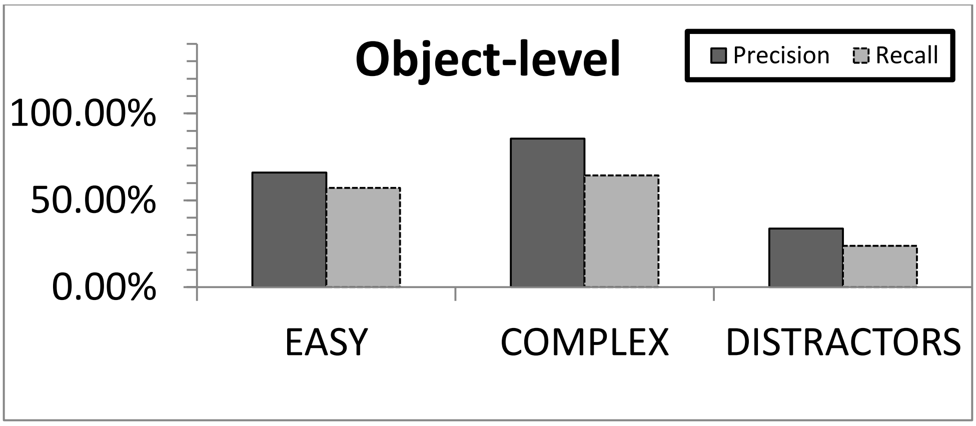
(d) Toothbrush head



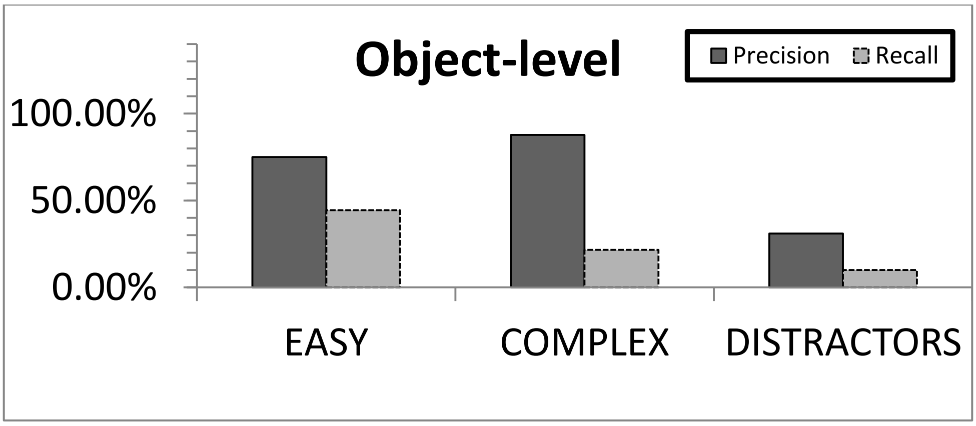
(e) Hand Gel



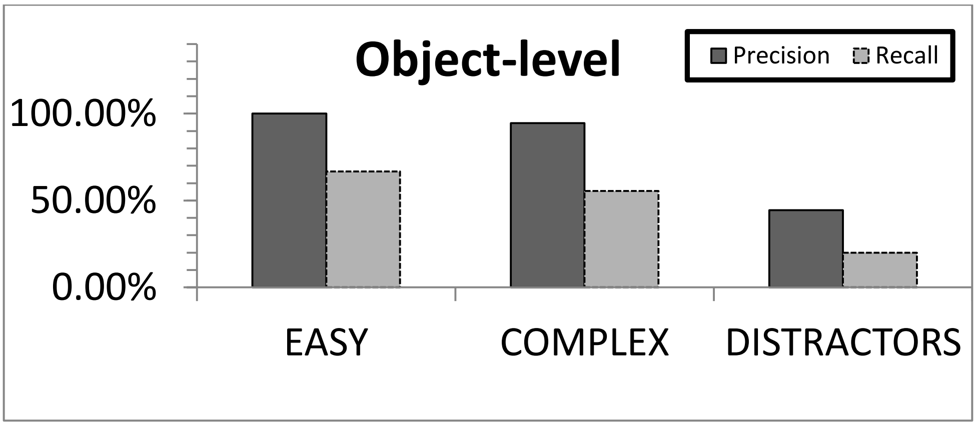
(f) Band-aid Box



(g) Large Pills

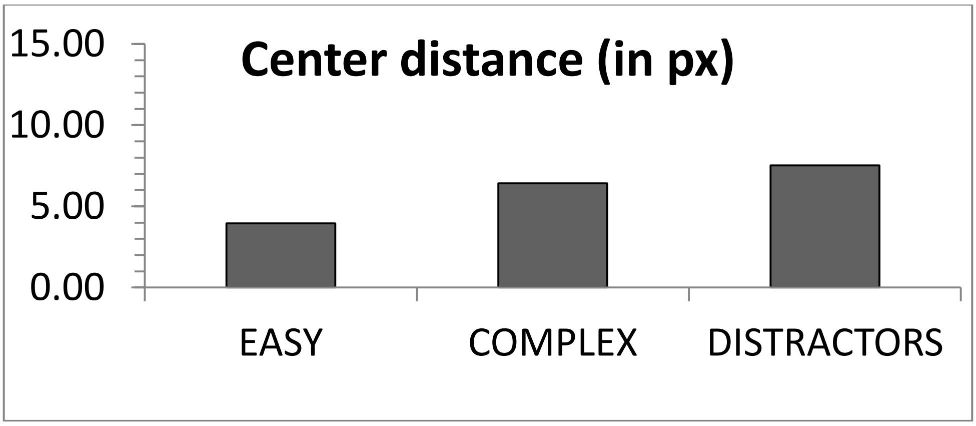


(h) Medium Pills

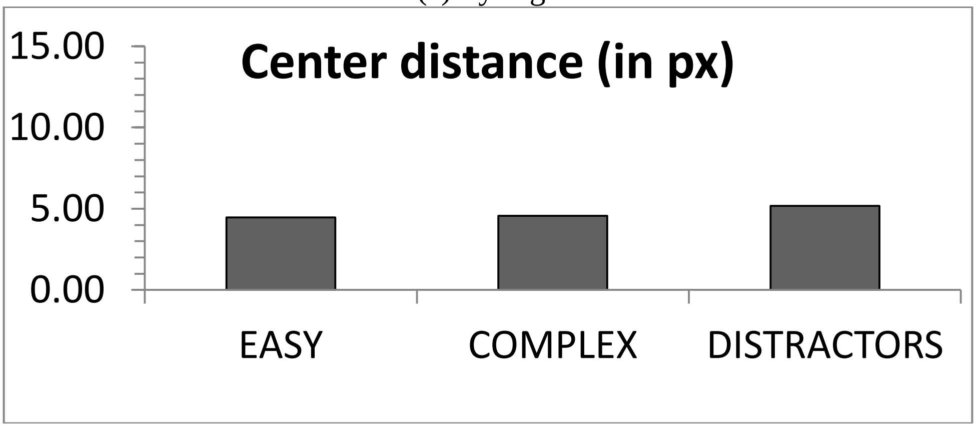


(i) Small Pills

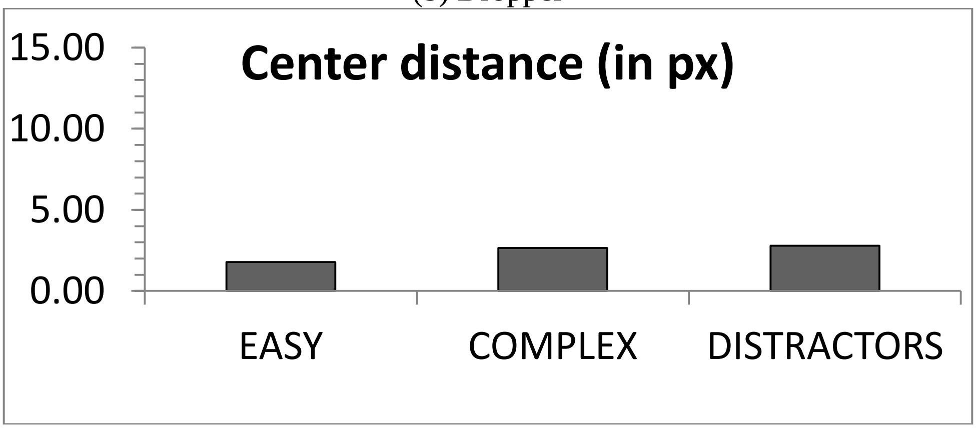
Figure 12 Histograms of center distance (in pixels)



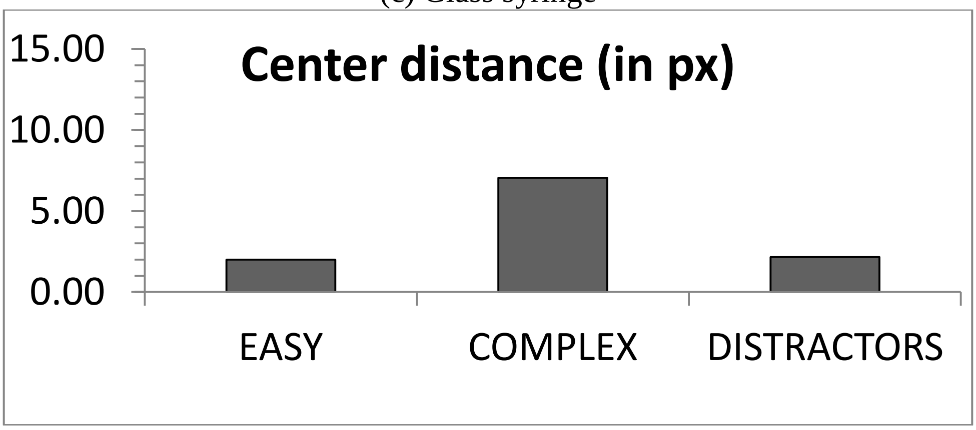
(a) Syringe



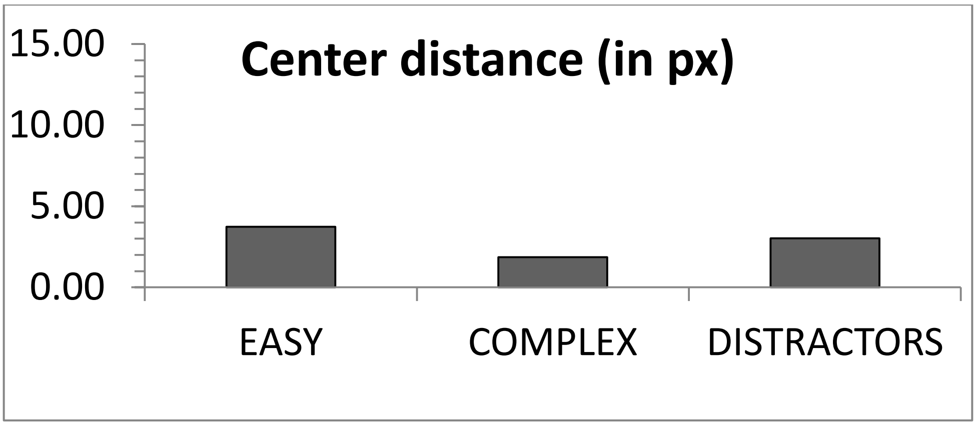
(b) Dropper



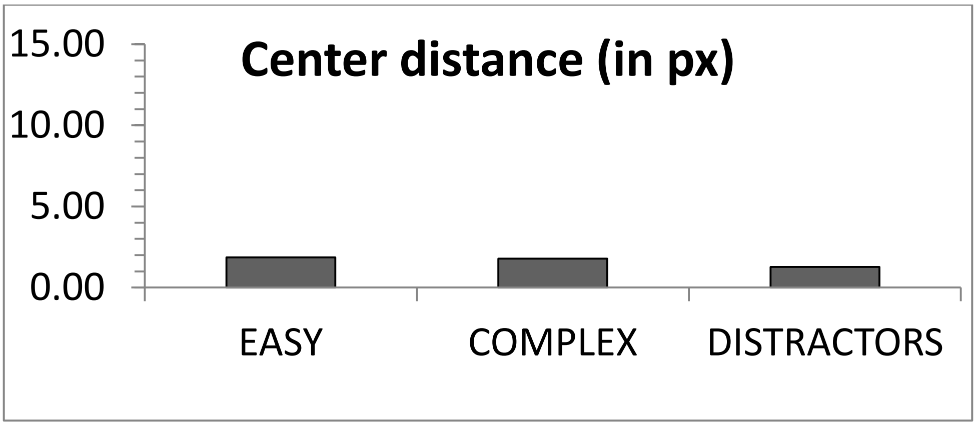
(c) Glass syringe



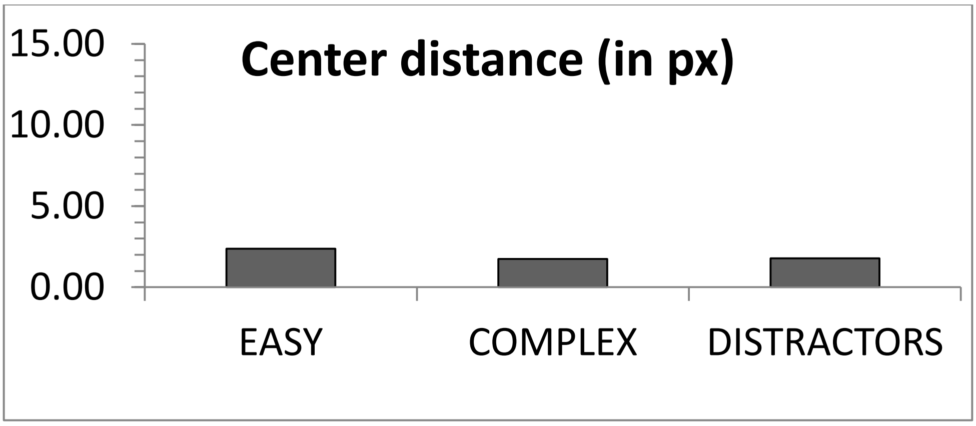
(d) Toothbrush head



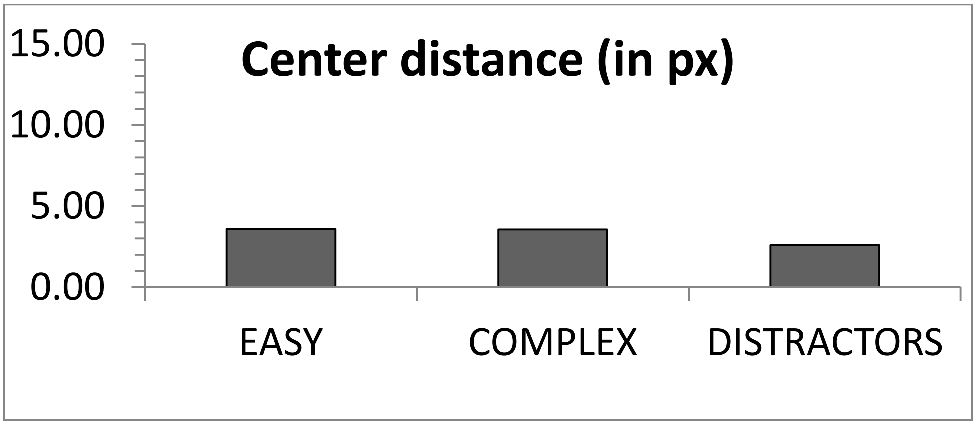
(e) Hand Gel



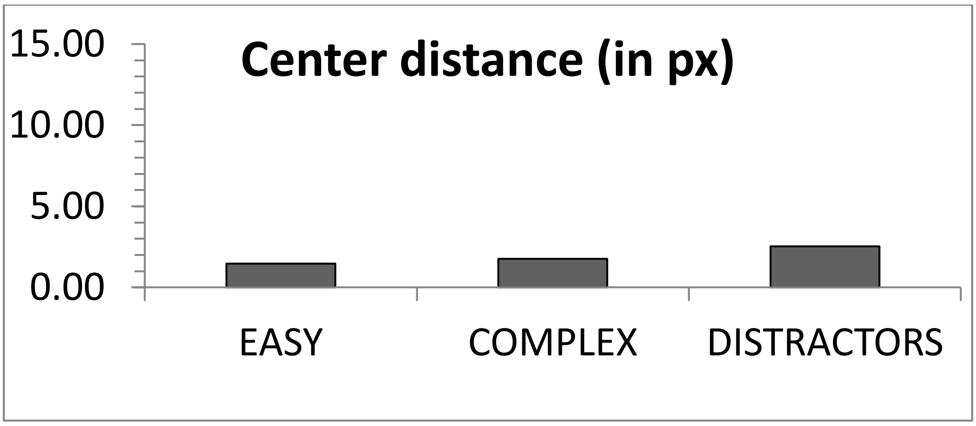
(f) Band-aid Box



(g) Large Pills



(h) Medium Pills



(i) Small Pills

Figure 14 Percentage of correct picking in the sequence experiment

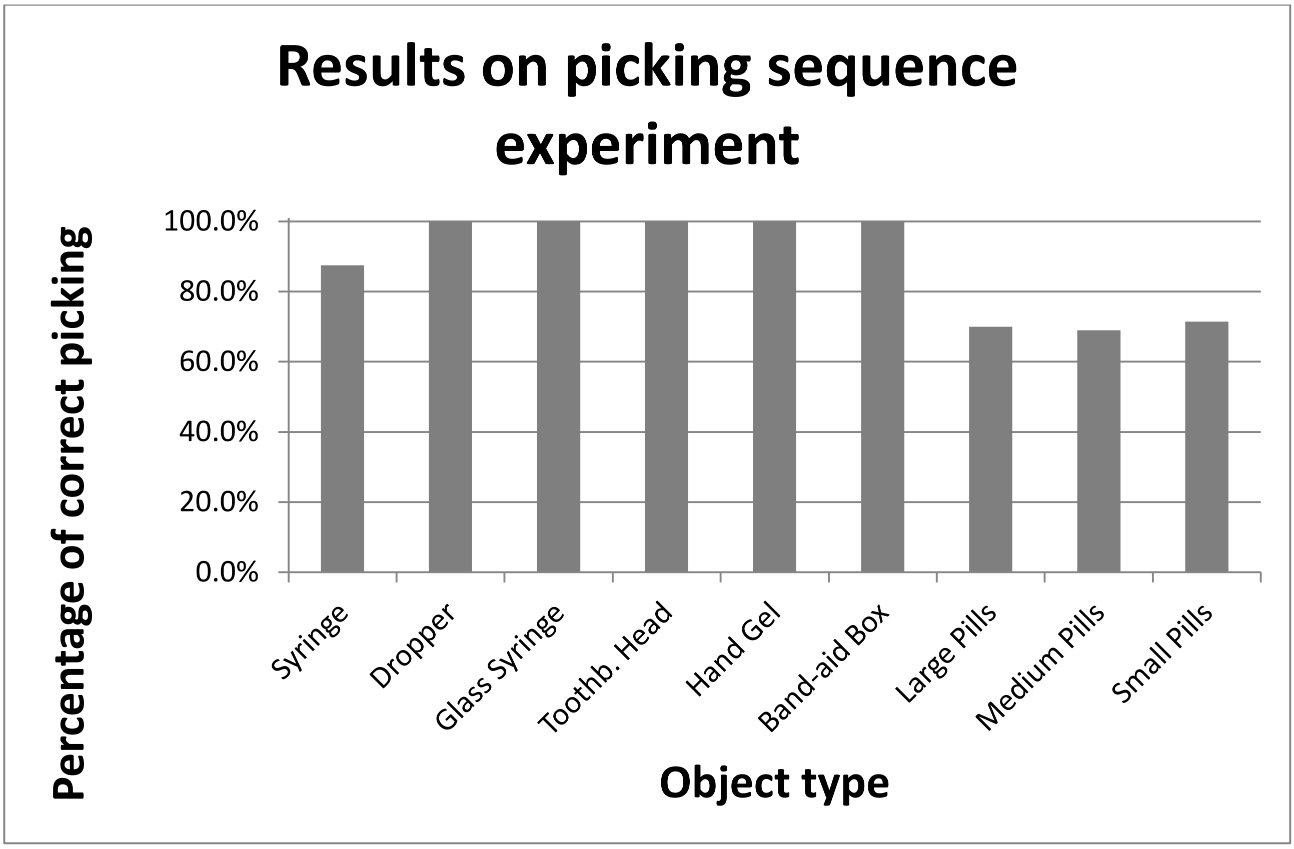


Table 1 Published approaches in the field of vision-based object grasping systems

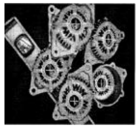
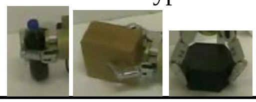
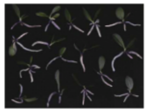
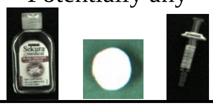
Paper ref. (year)	*Addressed objects*	*Note*	*Difficulties*							
			Distractors	Multiple Instances	Occlusions	Random Disposal	No control illumination	Different size objects	Transparent objects	Reflective objects
Rahardja & Kosaka (1996)	Alternator covers 	Use of stereo cameras	YES	YES	YES	YES	U	NO	NO	YES
Sanz et al. (1998)	Potentially any 	N/A	NO	NO	NO	NO	NO	YES	NO	NO
Bone et al. (2008)	Metal bracket and hex nut 	3D model acquisition + integration of structured light	NO	NO	NO	NO	NO	YES	NO	YES
Saxena et al. (2008)	Potentially any 	Not identifying objects, just grasping	NO	NO	YES	YES	YES	NO	YES	YES
Speth et al. (2008)	Several types 	3D model acquisition	NO	NO	NO	NO	U	YES	NO	NO
Huang & Lee (2010)	Tissue culture plantlets 	Use of stereo cameras	NO	YES	NO	NO	NO	NO	NO	NO
Proposed system	Potentially any 	Use of stereo cameras	YES	YES	YES	YES	YES	YES	YES	YES

Table 2 Summary of the types of objects used in the experiments

Name	*Texture*	*Size*	*Reflectivity*	*Transparency*	*Multi-face*	*Deformability*	*Difficulty*
	Positive	**Positive**	**Negative**	**Negative**	**Negative**	**Negative**	
Syringe	Very Low	Low	Medium	High	Very Low	Low	High
Dropper	Very Low	Very Low	High	Very High	Very Low	Low	High
Glass Syringe	Medium	Low	Low	High	High	Very Low	Medium
Toothb. Head	Very High	Medium	Low	Low	High	Very Low	Low
Hand Gel	High	High	Medium	High	High	Very Low	Medium
Band-aid Box	Very High	High	Very Low	Very Low	High	Very Low	Very Low
Large Pill	Very Low	Medium	Low	Very Low	Very Low	Very Low	High
Medium Pill	Very Low	Low	Low	Very Low	Very Low	Very Low	High
Small Pill	Very Low	Very Low	Low	Very Low	Very Low	Very Low	Very High

Table 3 Mean area in the case study

Name		*Name*		*Name*	
Syringe	14262 px	Toothb. Head	33375 px	Large Pill	19142 px
Dropper	10758 px	Hand Gel	24072 px	Medium Pill	11971 px
Glass Syringe	11435 px	Band-aid Box	30628 px	Small Pill	6413 px

Table 4 Accuracy at object level and center distance (both and measures).

Name	Precision	Recall		
	EASY			
Syringe	100.00%	77.78%	3.95	0,028%
Dropper	91.67%	100.00%	4.46	0,041%
Glass Syringe	100.00%	88.89%	1.78	0,016%
Toothb. Head	100.00%	100.00%	1.99	0,006%
Hand Gel	100.00%	66.67%	3.74	0,016%
Band-aid Box	100.00%	53.33%	1.86	0,006%
Large Pill	66.03%	57.14%	2.37	0,012%
Medium Pill	75.00%	44.44%	3.60	0,030%
Small Pill	100.00%	66.67%	1.46	0,023%
	COMPLEX			
Name	**Precision**	**Recall**		
Syringe	100.00%	57.14%	6.43	0,045%
Dropper	74.49%	53.33%	4.56	0,042%
Glass Syringe	94.32%	72.46%	2.65	0,023%
Toothb. Head	84.13%	70.00%	7.05	0,021%
Hand Gel	100.00%	50.00%	1.85	0,008%
Band-aid Box	100.00%	46.67%	1.79	0,006%
Large Pill	85.45%	64.29%	1.74	0,009%
Medium Pill	87.78%	21.67%	3.56	0,030%
Small Pill	94.44%	55.56%	1.76	0,027%
	DISTRACTORS			
Name	**Precision**	**Recall**		
Syringe	63.89%	61.90%	7.52	0,053%
Dropper	93.33%	48.89%	5.17	0,048%
Glass Syringe	97.62%	60.87%	2.79	0,024%
Toothb. Head	89.68%	60.00%	2.16	0,006%
Hand Gel	100.00%	30.00%	3.03	0,013%
Band-aid Box	100.00%	50.00%	1.26	0,004%
Large Pill	33.70%	23.81%	1.78	0,009%
Medium Pill	31.03%	10.00%	2.58	0,022%
Small Pill	44.44%	20.00%	2.53	0,039%

Table 5 Mean registered time in robotic picking workstation.

Name	Image acquisition [sec]	Image processing [sec]	Picking [sec]	Placing [sec]	Total time [sec]	Items per minute	*Comparison*
Syringe	0,0103	0,210	0,250	0,250	0,720	83	+55,42%
Dropper	0,0103	0,210	0,250	0,250	0,720	83	+55,42%
Glass Syringe	0,0103	0,430	0,250	0,250	0,940	63	+41,27%
Toothb. Head	0,0103	0,430	0,250	0,250	0,940	63	+41,27%
Hand Gel	0,0103	0,430	0,250	0,250	0,940	63	+41,27%
Band-aid Box	0,0103	0,430	0,250	0,250	0,940	63	+41,27%
Large Pill	0,0103	0,0983	0,250	0,250	0,609	98	+66,33%
Medium Pill	0,0103	0,0983	0,250	0,250	0,609	98	+66,33%
Small Pill	0,0103	0,0983	0,250	0,250	0,609	98	+66,33%

Table 6 Mean registered time in manual workstation through MINIMOST system.

Name	MINIMOST sequence	Object detection [TMU]	Picking [TMU]	Placing [TMU]	Total [TMU]	Total [sec]	Items per minute	*Comparison*
Syringe		6	10	28	44	1,58	37	-124,32%
Dropper		6	10	28	44	1,58	37	-124,32%
Glass Syringe		6	10	28	44	1,58	37	-70,27%
Toothb. Head		6	10	28	44	1,58	37	-70,27%
Hand Gel		6	10	28	44	1,58	37	-70,27%
Band-aid Box		6	10	28	44	1,58	37	-70,27%
Large Pill		6	16	28	50	1,80	33	-196,97%
Medium Pill		6	16	28	50	1,80	33	-196,97%
Small Pill		6	16	28	50	1,80	33	-196,97%

Table 7 Comparison between robotic and manual approaches in case of multiple iterations of the robotic system for complex objects.

Name	***2 iterations***		***3 iterations***		***4 iterations***	
	Items per minute	***Compar.***	**Items per minute**	***Compar.***	**Items per minute**	***Compar.***
Syringe	63	+41,27%	51	+22,22%	43	+9,52%
Large Pill	83	+60,24%	72	+54,17%	64	+48,44%
Medium Pill	83	+60,24%	72	+54,17%	64	+48,44%
Small Pill	83	+60,24%	72	+54,17%	64	+48,44%

Table 8: Mean registered time in manual picking workstation, while considering only correctly managed items.

Name	**Items per minute**	*Comparison*	**Error percentage [0,2%;1,5%]**	
			Items per minute while considering detection errors	*Comparison*
Syringe	37	-124,32%	36	-122,22%
Dropper	37	-124,32%	36	-130,56%
Glass Syringe	37	-70,27%	36	-75,00%
Toothb. Head	37	-70,27%	36	-75,00%
Hand Gel	37	-70,27%	36	-75,00%
Band-aid Box	37	-70,27%	36	-75,00%
Large Pill	33	-196,97%	32	-190,63%
Medium Pill	33	-196,97%	32	-190,63%
Small Pill	33	-196,97%	32	-190,63%

Table 9: Mean registered time in robotic picking workstation, while considering only correctly managed items.

Name	Image acquisition [sec]	Image processing [sec]	Picking [sec]	Placing [sec]	Total time [sec]	Items per minute	*Comparison*	Items correctly managed per minute [%]	Total time while considering detection errors [sec]	Items per minute while considering detection errors	*Comparison*
Syringe	0,0103	0,21	0,25	0,25	0,7203	83	55,42%	87,50%	0,7478	80	55,00%
Dropper	0,0103	0,21	0,25	0,25	0,7203	83	55,42%	100,00%	0,7203	83	56,63%
Glass Syringe	0,0103	0,43	0,25	0,25	0,9403	63	41,27%	100,00%	0,9403	63	42,86%
Toothb. Head	0,0103	0,43	0,25	0,25	0,9403	63	41,27%	100,00%	0,9403	63	42,86%
Hand Gel	0,0103	0,43	0,25	0,25	0,9403	63	41,27%	100,00%	0,9403	63	42,86%
Band-aid Box	0,0103	0,43	0,25	0,25	0,9403	63	41,27%	100,00%	0,9403	63	42,86%
Large Pill	0,0103	0,0983	0,25	0,25	0,6086	98	66,33%	70,00%	0,6412	93	65,59%
Medium Pill	0,0103	0,0983	0,25	0,25	0,6086	98	66,33%	68,97%	0,6423	93	65,59%
Small Pill	0,0103	0,0983	0,25	0,25	0,6086	98	66,33%	71,43%	0,6396	93	65,59%

Table 10: Unitary handling cost in manual picking system, by considering both an ideal environment without errors and detected errors

Name	Items per minute	Unit handling cost [€/pc]	Error percentage [0,2%;1,5%]	
			Items per minute while considering detection errors	Unit handling cost [€/pc]
Syringe	37	0,0122	36	0,0125
Dropper	37	0,0122	36	0,0125
Glass Syringe	37	0,0122	36	0,0125
Toothb. Head	37	0,0122	36	0,0125
Hand Gel	37	0,0122	36	0,0125
Band-aid Box	37	0,0122	36	0,0125
Large Pill	33	0,0136	32	0,0141
Medium Pill	33	0,0136	32	0,0141
Small Pill	33	0,0136	32	0,0141

Table 11: Unitary handling cost in manual picking system, by considering both an ideal environment without errors and detected errors

Name	Items per minute	Hourly automated picking system cost [€/h] 40 [€/h] Unitary handling cost [€/pc]	50 [€/h] Unitary handling cost [€/pc]	60 [€/h] Unitary handling cost [€/pc]	70 [€/h] Unitary handling cost [€/pc]	80 [€/h] Unitary handling cost [€/pc]	Items correctly managed per minute [%]	Total time while considering detection errors [sec]	Items per minute while considering detection errors	Hourly automated picking system cost [€/h] 40 [€/h] Unitary handling cost [€/pc]	50 [€/h] Unitary handling cost [€/pc]	60 [€/h] Unitary handling cost [€/pc]	70 [€/h] Unitary handling cost [€/pc]	80 [€/h] Unitary handling cost [€/pc]
Syringe	83	0,0080	0,0100	**0,0120**	0,0141	0,0161	87,50%	0,7478	80	0,0083	0,0104	**0,0125**	0,0146	0,0167
Dropper	83	0,0080	0,0100	**0,0120**	0,0141	0,0161	100,00%	0,7203	83	0,0080	0,0100	**0,0120**	0,0141	0,0161
Glass Syringe	63	0,0106	**0,0132**	0,0159	0,0185	0,0212	100,00%	0,9403	63	0,0106	**0,0132**	0,0159	0,0185	0,0212
Toothb. Head	63	0,0106	**0,0132**	0,0159	0,0185	0,0212	100,00%	0,9403	63	0,0106	**0,0132**	0,0159	0,0185	0,0212
Hand Gel	63	0,0106	**0,0132**	0,0159	0,0185	0,0212	100,00%	0,9403	63	0,0106	**0,0132**	0,0159	0,0185	0,0212
Band-aid Box	63	0,0106	**0,0132**	0,0159	0,0185	0,0212	100,00%	0,9403	63	0,0106	**0,0132**	0,0159	0,0185	0,0212
Large Pill	98	0,0068	0,0085	0,0102	0,0119	**0,0136**	70,00%	0,6412	93	0,0072	0,0090	0,0108	0,0125	**0,0143**
Medium Pill	98	0,0068	0,0085	0,0102	0,0119	**0,0136**	68,97%	0,6423	93	0,0072	0,0090	0,0108	0,0125	**0,0143**
Small Pill	98	0,0068	0,0085	0,0102	0,0119	**0,0136**	71,43%	0,6396	93	0,0072	0,0090	0,0108	0,0125	**0,0143**