Virtual environment for robotic assistance application

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Abstract. A virtual environment presents several advantages in the training of assistive robots based on artificial intelligence techniques, it let iterative probes, tunings, and establish previous conditions for real environments. Convolutional neural network (CNN) is the most representative architecture employ to object recognition, this is necessary for a machine vision system for assistive robots. A Fast R-CNN is trained in a virtual environment for an application of tools ordering with an assistive robot obtaining 98% precision in the execution of this task, with five virtual tools.

Keywords: Fast R-CNN, robotic assistance, virtual environment, virtual tools.

1 Introduction

Assistive robotics and intelligence artificial techniques has let to increase the variety and quality of services that a robot can deliver to users or industrial process. Some applications like the Human-robot interaction in open industrial cells [1] and learn to grasp an arbitrary object from visual input [2] shows the actual relevance about this topic. On the other hand, the task of organizing objects also involves the use of detection algorithms and element recognition to give the robot the ability to visualize and detect all the objects that must be sorted within a workspace, algorithms like the convolutional neural networks (CNN) [3].

Faster R-CNN is one of the main architectures of CNN based on regions and used at the top of the state of art. Its application is very diversified, like in medicine with heart localization target [4], likewise in applications on precision agriculture in pest detection [5]. In the present work, Faster R-CNN are used for the detection and classification of up to 5 different tools to be sorted on a virtual space. Faster R-CNN is used to detect and organize objects and extract the locations and orientations of each of them [6].

In this sorting algorithm, up to 5 different tools are located in a row in a simulated environment for evaluate the trained network previous its implementation in a physical one, where there is no specific site for each type of tool, but they are organized one next to the other. This application allows the ordering of multiple elements within a workspace automatically, eliminating the need to employ human personnel for this task and ensuring constant distances between objects. It is a novel method of ordering
is presented, based on the distance of each tool with respect to the right side of the
table and the distances between them, where artificial intelligence techniques.

2 Material and Methods

The system detect and classify up to 5 types of tools where their locations, orienta-
tions and approximate dimensions of the space they occupy in the work environment
are extracted, and a manipulator is programmed to perform the grip and sort of the
detected tools, placing them next to each other with the same orientation. Fig. 1 shows
the flowchart of the algorithm, from the process of detection and classification of
tools on the environment, to the final ordering of all the elements.

![Algorithm flowchart](image)

**Fig. 1.** Algorithm flowchart.

The first step is to detect and classify all the tools using a Faster R-CNN. In this
step, it is gotten the number of tools found, the position of each of them, their orienta-
tions and the width and height dimensions of the space they occupy over the work
area.

In the second step, the sorting tool algorithm is executed, which reorders all the
tools found on the table, leaving them at a certain distance between them and at the
same height and orientation. To achieve this, the information extracted from the tools
in the previous step is used, and they are ordered one by one, from right to left, leav-
ing the first tool near the right margin of the table.

In the third step, it is looked for new tools to be sorted. Once grabbed, the ordering
algorithm is again used to locate the new tool at the end of the row, at the previously
determined distance. The cycle is repeated until the 5 tools are arranged on the table.

The working space was organized as shown in Fig. 2, the virtual environment was
implemented in MATLAB, like the Faster R-CNN programming.
The architecture of the network used is shown in Fig. 4, which was trained with a total of 716 images where each of them contains the 5 tools to be classified and all were taken over the work area established for the application, where [3] explains the different layers of a convolutional neuronal network, which make up the Faster R-CNN. The respective confusion matrix shows an accuracy of 70.8%, this behavior was obtained from test the network with 80 test images, each with the 5 tools.

Fig. 2. Virtual elements.

For the detector and classifier by Faster R-CNN used in the recognition of, it was possible to locate, with some difficulties, the objects to be sorted, reaching a general result such as shown in Fig. 4, where the organization of each tool is done at different times and some confusion between scalpel and screwdriver was detected, making the success around 98%. Table 1 gives some examples of algorithm validation, with 20 tests for the organization of the tools, its hits, and average time.

The manipulator does not have a degree of freedom that allows rotating the gripper to adjusting the orientation of each tool before ordering it, for that reason, in the simulation all tools are parallel to each other.

3 Results

Fig. 3. Architecture of the Faster R-CNN.
Table 1. Tools manipulations results.

<table>
<thead>
<tr>
<th>Tool</th>
<th>Hits vs Trials</th>
<th>Average time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Screwdriver</td>
<td>19/20</td>
<td>1.23 seg</td>
</tr>
<tr>
<td>Scissor</td>
<td>20/20</td>
<td>1.28 seg</td>
</tr>
<tr>
<td>Scalpel</td>
<td>18/20</td>
<td>1.14 seg</td>
</tr>
</tbody>
</table>

4 Conclusion

The detection and classification properties of the Faster R-CNN allow obtaining a clear knowledge of the workspace, reducing to the maximum the number of false positives, and allowing organize assertively the tools through the robotic manipulator.

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References