ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
Tome XIV [2016] – Fascicule 1 [February]
ISSN: 1584-2665 [print; online]
ISSN: 1584-2673 [CD-Rom; online]
a free-access multidisciplinary publication of the Faculty of Engineering Hunedoara

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INTELLIGENT CONTROL OF MOBILE ROBOT FOR OBJECT RECOGNITION AND GRASPING

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ABSTACT: In this paper, the problem of robot vision system is considered as a part of hierarchically highest level of control that is used for object recognition and that allows adequate and reliable robotic grasping. Thus, the application of an intelligent classifier is proposed in the object recognition process for an advanced and robust robot vision system. This novel technique allows 3D object reconstruction with accurate determination of position and orientation of a rigid body that can help in deciding where to grasp object with a robot arm. Classification is performed using features obtained from segmented image after preprocessing, image segmentation and post-processing. Such an image combined with classification results enables accurate 3D object reconstruction that is crucial for grasping problem.
Keywords: Robot vision, Intelligent algorithms, Classification, Object recognition, Robot Grasping

1. INTRODUCTION

One of the key requirements in the field of service robotics is the robust perception of the robot environment, which is necessary for autonomous object manipulation [1,2]. A robot vision system is used to robustly analyze the images of complex scenes where the objects to be recognized are surrounded by a variety of other objects. As well as being robust against cluttered scenes, a robot vision system has to be robust against unpredictability in the appearance of objects due to external influences, such as variable illumination. However, in spite of the significant work on the development of robot vision systems in recent years [3, 5], recovery of 3D shape is a critical problem in many vision application domains such as object modeling, scene understanding and high level visual activity recognition or robotics applications [2]. Obtaining a precise and accurate depth map is the ultimate goal for 3D shape recovery and 3D image reconstruction.

The main idea in this paper is the use objects segmented form depth image, extract features and use neural network classifier for object recognition. The proposed methods are a novel alternative to the conventional approach of using additional sensors or introducing a more controlled environment [8,9]. Some of the objects to be recognized may be located in cluttered environments, for example there may be several objects in the fridge or on the book shelf. Hence, the robot vision system must be robust enough to cope with the clustered environment (complex scenes) and with a variety of different objects as well as with different appearances of the same object in different lighting conditions that arise during the robot operation, ranging from daylight to artificial light.

2. EXPERIMENTAL SETUP

For development of reliable computationally intelligent object recognition in robotic vision, the system FRIEND (Functional Robot arm with frIENdly interface for Disabled people) has been mainly used, which has been under continuous development within different projects at the Institute of

Automation of University of Bremen since 1997 [2,6,7,10], where University of Niš, Faculty of Mechanical Engineering, has been participating in research since 2009. It is an intelligent wheelchair-mounted manipulator consisting of a 7 DoF (Degrees of Freedom) manipulator mounted on an electrical wheelchair and a computer based manipulator control (Figure 1).

A Bumblebee® stereo-camera system is mounted on a special rack behind the user, above his head, as illustrated in figure 1. Using a special input device such as a chin joystick, the user navigates the system in front of the container containing objects related to the particular working scenario (for example fridge in the "serving a drink" working scenario). The stereo cameras view the scene in front of the robotic system including the container with the objects and the manipulator. Obtained stereo images are processed in a sequence of image processing operations aiming at the extraction of features needed for both 2D object recognition in stereo images and 3D stereo reconstruction of the manipulator's environment.

3. OBJECT SEGMENTATION

Initial step in object recognition is determining depth image from stereo image captured with Bumblebee stereo camera, removing the background and determining clustered regions. For this purpose algorithm developed by researchers from Institute for Automatics TU Bremen was used [10]. Initial segmentation results are presented in Figure 2.

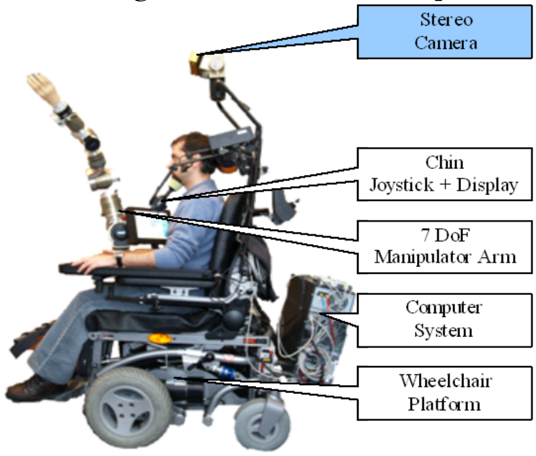

Figure 1. The assistive robotic system FRIEND

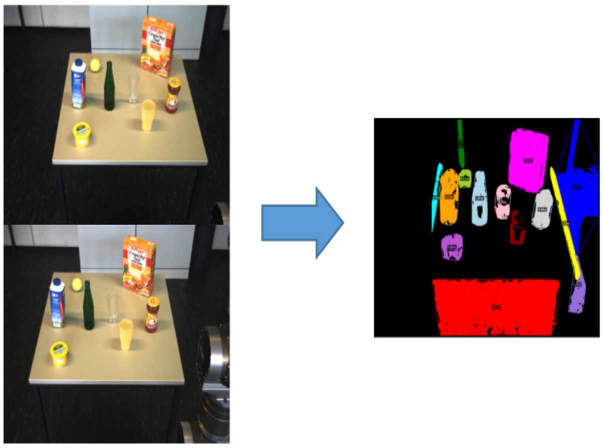

Figure 2. Depth image with subtracted background

To achieve robust object recognition several object features and shape descriptors should be calculated. The spatial connectivity of a segmented object pixel and its neighborhood-segmented pixels can be expressed by the following measure $I=-\log_2 p_8,\ I(0)=0$,here p_8 is segmented pixel probability estimate, surrounded with 8 segmented pixels in its 8-pixel neighborhood:

$$p_8=\frac{\text{no of seg pixels surrounded with 8 seg pixels}}{\text{total no of segmented pixels}}.$$

The proportionality of a region of connected segmented pixels can be expressed as $p_r = h/w$, where h and w, are respectively height and width of the bounding box of the segmented region. The bounding box is the smallest rectangle containing the segmented region.

Hu moments are invariant coefficients which are derived from moments of the image region [4]. In the presented system 7 Hu moments were analized:

Table 1. Object segmentation and feature extraction results

	Bottle (Class 1)	Carton (Class 2)	Glass (Class 3)	Jar (Class 4)
				
I	0.2144	0.0827	0.3225	0.1428
p_r	2.7338	2.3343	1.1534	1.4623
M_1	0.7468	0.7424	0.7558	0.7479
M_2	2.6109	2.5318	2.6456	2.6100
M_3	6.6204	5.1435	7.2942	6.6940
M_4	5.6006	5.3548	5.9980	5.7246
M_5	11.561	-10.7033	-12.8466	-12.3733
M_6	6.9190	-7.0355	7.3234	7.0721
M_7	11.770	-10.5647	-13.6693	-11.7935

In Table 1 all 9 extracted features for four objects found in one scene are presented. Each of 9 extracted features are possible classificator inputs. Based on expert knowlege and trial and error method, first 7 features were used as classifier input.

4. ARTIFICIAL NEURAL NETWORK CLASSIFIER

All classification algorithms are based on the assumption that the image in question depicts one or more features and that each of these features belongs to one of several distinct and exclusive classes. Artificial neural networks (ANN) are parallel, distributed, adaptive information-processing systems that develop their functionality in response to exposure to information, and are used for problems of classification, pattern recognition, prediction and others [9]. Resembling the human brain, which learns by adjusting the number and strength of synaptic connections, ANN is an adaptive system that changes its structure based on information that is processed within the network during the learning stage.

The ANN used in this study was a standard feed-forward, back propagation neural network with three layers: an input layer, a hidden layer consisting of 10 hidden neurons and an output layer. Input network variables were two object features, while three network outputs represent probabilities of object belonging to each of the four classes (Table 1). The ANN classifier is shown in Figure 3. For training, the back propagation scaled conjugate gradient algorithm that updates weight and bias states according to Levenberg-Marquardt optimization was used, while the mean squared error was used as a performance measure during training.

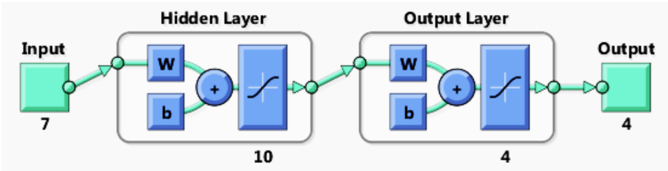

Figure 3. Neuro classifier structure

For ANN classifier more demanding dataset of 940 training vectors was used containing more severely occluded object features, that was randomly divided into training, validation and testing sets. The training set (658 samples) was presented to the network during training, and the network was adjusted according to its error. The validation dataset (141 samples) was used to measure network generalization, and to halt training when generalization stopped improving.

Finally, the testing dataset (141 samples) had no effect on training and so provided an independent measure of network performance. Classification confusion matrices are presented in Figure 4 showing that even under demanding conditions classification accuracy is high.

Figure 4. ANN classifier results for a demanding data set

5. CONCLUSION

Robustness of a robot vision system against variable illumination is achieved by including intelligent segmentation algorithm, providing reliable feature extraction neural classifier that is an important part of the proposed object recognition method. Computationally intelligent classifiers have experimentally proven their robustness which goes along with capability to efficiently deal with significantly increased number of object classes in the future development and/or increased dimension of feature space vector by adding more features.

To further address the problem of recognizing and reconstructing real-world objects in cluttered environments to enable service robot to grasp the objects and manipulate them, computational intelligence approaches can be combined with a novel approach that combines disparity segmentation method with the closed-loop color region based segmentation. Starting from the segmented object in both stereo images, the 3D contour of the object is generated and the object geometry could be recovered from it by means of computational intelligence to provide for robustness.

Note

This paper is based on the paper presented at The 12th International Conference on Accomplishments in Electrical and Mechanical Engineering and Information Technology – DEMI 2015, organized by the University of Banja Luka, Faculty of Mechanical Engineering and Faculty of Electrical Engineering, in Banja Luka, BOSNIA & HERZEGOVINA (29th – 30th of May, 2015), referred here as[11].

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