Echoic Rescue Team Description Paper RoboCup 2018 Virtual Robot League

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Abstract. This paper is a short review of the proposed approach developed by the Echoic team for participation in RoboCup 2018 Rescue Simulation League, Virtual Robot Competition. Our focus is on improving the problems of previous years, including multi-robot exploration and visual victim detection.

Keywords: Robocup 2018, Virtual Robot, ROS, Gazebo, Navigation, Multi-Robot Exploration, SLAM, HOG, Faster-RCNN.

1 Introduction

In the world today, many human and financial costs are spent to save people in various critical situations. Prominent example of this situation is earthquake. In order to reduce costs, especially in terms of casualties, many researchers are trying to get robots one day to save lives. The RoboCup Virtual Robot league has challenged this problem in a simulated environment in which robots should explore the disaster environment and find the victims.

Our team, which has been participated in the International RoboCup Competition since 2016, is made up of students driven by the goal of creating a team of intelligent robots.

Given our main goal of improving robots' performance, in the new part of our research, in order to reduce time wasting, less involvement in the framework programming, and focus on increasing our algorithms' performance, we went on to use the SOSVR[5] team base code[1], which have programmed a robust framework.

Major additions and unsolved challenges compared to previous years are:

1. Using better computer vision algorithms like CNN's[2] to improve detection accuracy.

[1] github.com/SOSVR/base_code-v2.git
[2] Convolutional Neural Networks

2. Improving multi-robot exploration algorithm.
3. Implementation of a GUI[3] for the human agent to simplify special tasks like parameter tuning and sensors calibration.

2 Proposed Approach

In this section, we want to explain the innovations, improvements, and the things we want to do for future. This year, our main focus is on multi-robot exploration and victim detection tasks.

2.1 Multi-Robot Exploration

Multi-robot exploration, considers minimizing the overall exploration time of an environment with a team of robots. So the robots should hold the areas they have already tracked and construct a global shared map to know which locations from whole environment have been occupied before and which not.

For a self-map generation, we use ROS implementation of slam_gmapping[2] that creates a 2-D grid map from laser range scanner and collected position data by the robot. Using map_merger[3] package, a same world model is constructed and shared between robots. This shared map is supposed as an input for Blatt et al.[24]'s novel method that combines the multi-agent Flood algorithm with famous Frontier-based exploration[23] strategy and is being implemented. The result of this algorithm is a part of the map that should be explored next.

2.2 Victim Detection

The main task of rescue robots is to find victims as many as possible and the victims' location should be marked on the generated map autonomously. Detecting people by a moving robot with a monocular camera is still a very difficult and open problem. Given the fact that the use of RGB-D cameras like Kinect, which makes the detection task easier, is not attached to the defined robots, we have to use a two-dimensional image processing approach for our purpose. Our approach, as is shown in Fig. 1, is like the vision system of most robots, consists of three steps:

1. Preprocessing the image for noise reduction.
2. Image Segmentation and ROI[4] detection to reduce the search space and improve the whole system performance both in terms of time and accuracy.
3. Applying detection and recognition algorithms on the detected ROI to validate object type for each region.

[3] Graphical User Interface
[4] Region's of Interest's

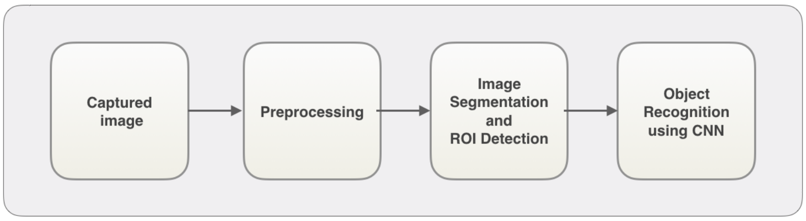

Fig. 1. Vision System Pipeline.

In **preprocessing** task, we use smoothing, erosion and dilation filters to remove image noise and improve the success of the subsequent steps.

In **Image Segmentation and ROI detection** section, the focus on many studies like Ma et al.[10] and Fan et al.[11], has been on edge-based color aided methods. But, most of these methods can not be applied for detection of objects' bounding box with complex patterns like a human body, and a machine learning approach must be used. In this category, Viola-Jones[6] is an example that uses Haar feature-based cascade classifiers for object detection. Yolo[20] is a state-of-the-art real-time object detector that uses CNN's to predict objects' boundary and class. The most famous and novel approach is faster-rcnn, introduced by Ren et al.[7], that includes a RPN[5] to find ROI and an Object Detection Network to determine each region belongs to which object.

For **Object Recognition**, there are many classifiers like SVM[6], Decision Tree, Random Forrest, and Neural Networks for training based on low-level features that can be extracted in variety of ways such as HOG[7], SURF[8], and SIFT[9] feature descriptors or CNN's. Results of the annual ImageNet[9] challenge proves the truth that CNN's are more accurate and reliable in this case.

Given that we do not have a good hardware system, after evaluation of mentioned methods, in terms of accuracy and time, we decided to use Yolo[20] that results in good accuracy although it requires less computational resources. To train our model, we had a dataset from the previous year, contains 5800 positive and 8200 negative images, from different angles.

Accuracy analysis of live video-based image processing methods using common evaluation metrics(precision, recall and etc.) is not necessarily the right thing. Like our model that is 75% accurate, but as is shown in Fig. 2, gives a lot of false positives and fails to predict the most obvious scenarios. So more works has to be done on it.

[5] Region Proposal Network
[6] Support Vector Machine
[7] Histogram of Oriented Gradients
[8] Speeded Up Robust Features
[9] Scale-Invariant Feature Transform

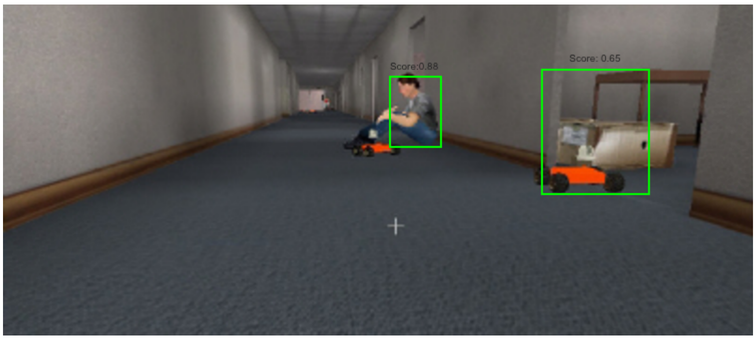

Fig. 2. A test case from our model that gives true positive and false positive output. Original image from robocup.org/leagues/27.

2.3 Behavior and Decision Making

For creating robot behavior, we use SMACH[4] library, that allows you to design, maintain and debug large, complex hierarchical state machines.

2.4 Human-Robot Interface

Using Qt framework, a control panel is developed to simplify the interaction between a human agent and robot. A part of developed interface is shown in Fig. 3.

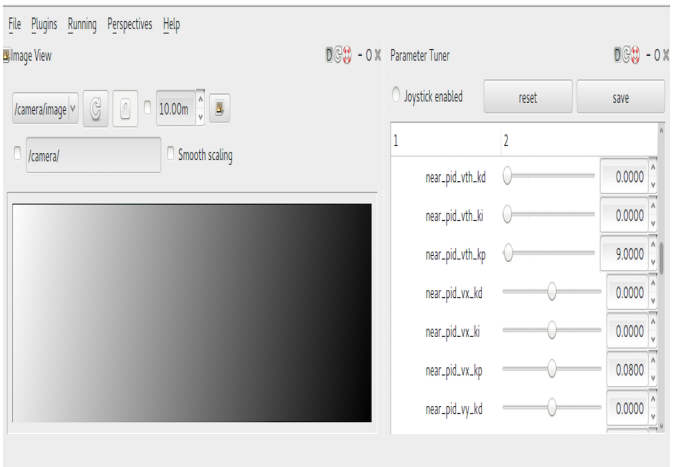

Fig. 3. A screenshot from rqt panel, we can simply tune the robot parameters using Parameter Tuner panel.

3 Conclusion

In this paper, we presented our ideas for improvement of robots' performance, to compete in the international RoboCup competition. Some of them are under development and a lot of work is needed to achieve the main goal. The goal that many people in the world are looking for and that is saving lives.

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