DOI: 10.20396/revpibic2720192900

Humanoid robot localization in a soccer field using Deep Learning

Gabriel Previato de Andrade*, Esther Luna Colombini

Abstract

With the evolution of humanoid robotics and its increasing use in diverse environments and tasks, it is imperative that the robot can interact with the environment and, therefore, understand it accurately to execute decision making.

In this work, we presented the process of collecting a new dataset for simulated soccer scenes. We simulated the RoboCup Humanoid challenge and collected over 200k images that contain up to 4 classes of objects, depth estimation, and bounding boxes. We then trained a modified multiclass version of J-MOD2 to validate the dataset and provide the landmarks distances to a Monte Carlo localization algorithm in order to estimate the robot position on the field.

Key words:

Localization, Deep Learning, Robotics

Introduction

Autonomous Location in robots is one of the great challenges faced by Robotics since, in order to perform high-level tasks such as playing football autonomously, robots must be able to locate and navigate safely through their operating environment. More recently, new approaches that make use of Machine Learning techniques for the extraction of characteristics of images, and then using these characteristics for localization have been considered. In this project, we create a simulated soccer dataset with RGB, Depth images, and obstacles annotations. Then we evaluate the convolutional neural network (CNN) proposed by [1] in our created dataset, where given an input image, the CNN outputs every obstacle in the image and its distance. Finally, we propose a multiclass approach to the above CNN, which we called Multiclass Obstacle Detection and Localization (MODL) in order to give the obstacle class and distance, feed a Monte Carlo particle filter to get robot position.

Results and Discussion

The SSNDa (Soccer Simulated NAO Dataset) is a simulation-generated dataset that contains more than 200k images and objects annotations from scenes extracted from a soccer simulated scenario that can be easily increased or modified. It consists of RGB images of a robot soccer field, associated depth gray-scaled images, and text files with information of the objects in the images.

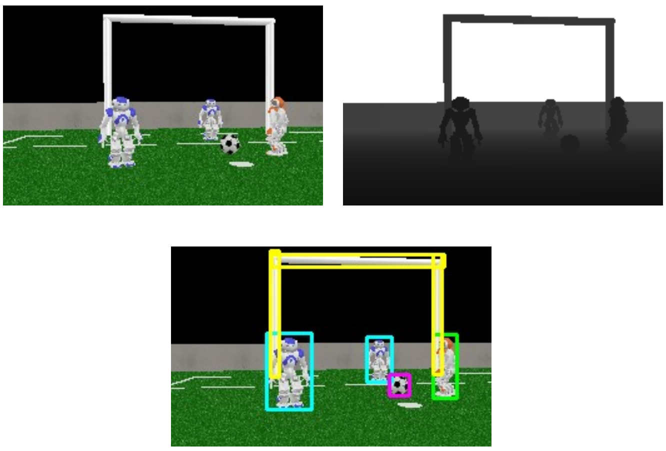

Image 1. RGB image, depth grey-scaled image, RGB image with the objects' bound box colored by classes.

We trained and evaluated in our dataset, the original J-MOD2 architecture and our modified multiclass architecture for 2, 3 and 4 classes. The results for the obstacle detection branch are shown in Table 1.

Table 1. Detection results (Higher is better)

	J-MOD2	MODL 2 classes	MODL 3 classes	MODL 4 classes
Detection IOU	78.15%	80.09%	78.11%	77.55%
Detection Precision	87.29%	96.68%	86.24%	85.87%
Detection Recall	90.14%	96.94%	86.56%	86.30%

We then tested our robot localization using a Monte Carlo filter particle. We tested in 2 scenarios, the robot running from one side of the field to the other seeing only the goal, and the robot running from one side of the field to the other seeing the goal, 2 static robots, and a ball. For each scenario, we ran the simulation 20 times.

The mean error in x-axis and y-axis and orientation (θ) for the robot position for both scenarios are showed in Table 2.

Table 2. Robot position mean error (Lower is better)

	Error in x (m)	Error in y (m)	Error in θ (rad)
Scenario 1	0.31	0.34	0.17
Scenario 2	0.23	0.22	0.13

Conclusions

Our proposed multiclass architecture shows better results in our dataset than the original architecture. Our localization results have better results than our previous work [2], although it needs improvements to achieve state-of-the-art results.

Acknowledgement

The authors gratefully thank CNPq for the support and funding.

[1] Mancini, M.; et al. J-MOD2: Joint Monocular Obstacle Detection and Depth Estimation. **2018**

[2] Andrade, G. P. de; Colombini, E. L. Localização No Futebol De robôs Humanoides. **2019**.