A Fast and Accurate Cognition Module for Humanoid Robots

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1 Introduction

In this research, we implemented a high-speed cognition module for AUTMan Humanoid Robotic Team. We the outputs(ball, Goalposts, Lines, Center Circle and Obstacles) of this system as inputs for localization and behavior modules of the robot. The challenges of this project are:
1- Humanoids suffer from low-frequency processors, like our platform which has an Intel Celeron Dual Core 1.10GHz processor.
2- Although robots in the soccer game field are placed in a high color information environment, Many objects in the field have similarity in terms of color. This problem makes us use an edge-based color-aided method.
Despite these problems, our algorithm has good accuracy and average frequency of the system is between 25-30 Hz which seems appropriate for Humanoid robots. In the next section, we will explain our proposed approach. Give notice that this report is written after 2017 Nagoya RoboCup and acceptance of our paper (1) in RoboCup symposium. That's why some parts of this report are very similar to our paper.

2 Proposed Approach

An overview of our system is shown in Fig. 1. A wide-angle YUV422 image is the input of our system. To construct a color classified image, set of random pixels are selected directly by a human agent in the image and a look-up table is created based on selected pixels range. This table is a mapping from YUV color space to a set of specific colors and assigns a class label(green, black, white or unknown) to each pixel.
To use edge based image segmentation and Hough Transform algorithms, we compute a binary image which describes edge intensity of each pixel in a given raw image. A grayscale image is generated by extraction of the Y channel. Afterwards, we compute the Scharr gradient operator on the grayscale image which results in the desired binary image. The new images compared to the camera image can be seen in Fig. 2.

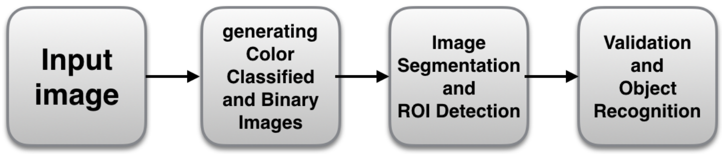

Figure 1: Overview of our system.

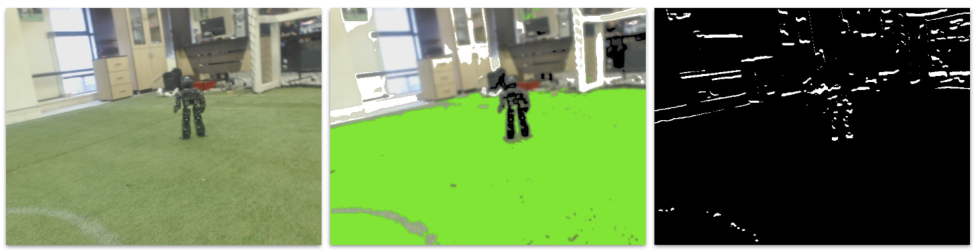

Figure 2: Left: system input in RGB format. Middle: color classified image. Right: binary image, the original picture belongs to (1).

2.1 Regions of Interests Detection

Reduction of the search space can increase the performance of the whole system, both in terms of time and accuracy. In order to find regions of interests (ROI), first, a vertical scan line runs inside the binary image to find pixels with high edge intensity. These edge spots build ROI boundaries and have the potential to construct the same shape. Then, based on two different approaches we find related spots and connect them to build the boundary of the objects, like a ball, the lines, the goals and the obstacles (Fig. 3). The first approach is the Euclidean distance of selected spots in the X and Y directions, and the second one is the size and the color of the area around them that can help identify which object the spots belong to. For example, in the case of obstacle detection, after perception of the black area around two adjacent spots inside the big green space and due to the fact that robots should have black feet in the RoboCup humanoid league, it can be concluded that considered boundary and it's edge spots belong to the robot feet. To extract the proposed region for a robot, our algorithm moves from the region of the detected feet to left and right until a continues green region according to a threshold is being detected. Then, we crop a rectangle from left most points to right most points in the X-axis and from foot to a horizontal line (computed from robot structure) in the Y-axis. Regions inside other bigger bounding boxes are omitted from the set of proposed regions. A sample from the detected region of the other objects is shown in Fig. 4.

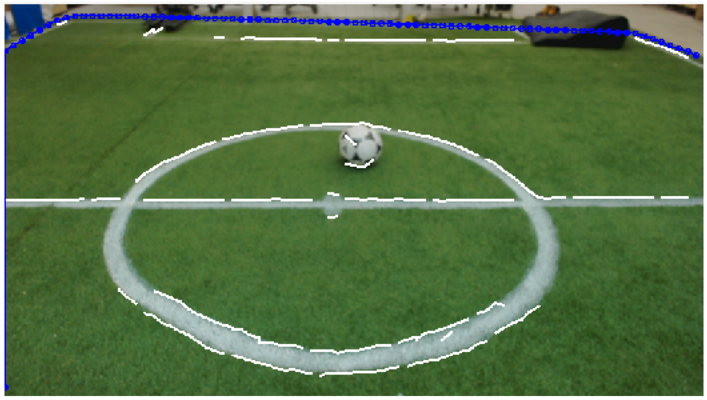

Figure 3: Detected boundaries of objects.

2.2 Contour analysis and Object detection

This module deals with feature extraction of image regions which detected in the previous stage, rather than straightforwardly extracting features calculated from the whole image. For example, we can't use Hough-Transform algorithms straightly in the whole image because they are expensive in terms of time.

There are four sub-layers: Ball Detection, Line Detection, Goal Post Detection and Obstacle Detection.

For **Ball Detection**, first, for each region of interest, we use Hough-Circle algorithm to check circularity of the region. Another important filter we used was the color histogram of the detected shape, According to this point that half the color of the ball is white, this was an important filter in our case. We also tested "haar-like features" in a form of cascade classifier for detection of the ball. The algorithm accuracy was great, but the algorithm was too slow in our processor and we were dissuaded to use it.

Using these steps, we detect the ball at a distance of 4 meters.

For **Lines and Goal-Posts Detection** tasks, we used the accurate and fast algorithm of (2) which is based on geometric calculus.

In the task of **Obstacle Detection**, a Deep Convolutional Neural Network is used to validate a detected region of interest if the region is an obstacle or not. A complete description of this step is here (1).

Using Kalman Filter in each section made our algorithm robust and more accurate. Fig. 5 shows detected objects from Fig. 3 detected regions.

3 Conclusion

The explained algorithm is fast(25-30 Hz frequency) in our platform processor(Intel Celeron Dual Core 1.10GHz processor). One of the benefits of our algorithm is that rarely gives false positives and is highly accurate.

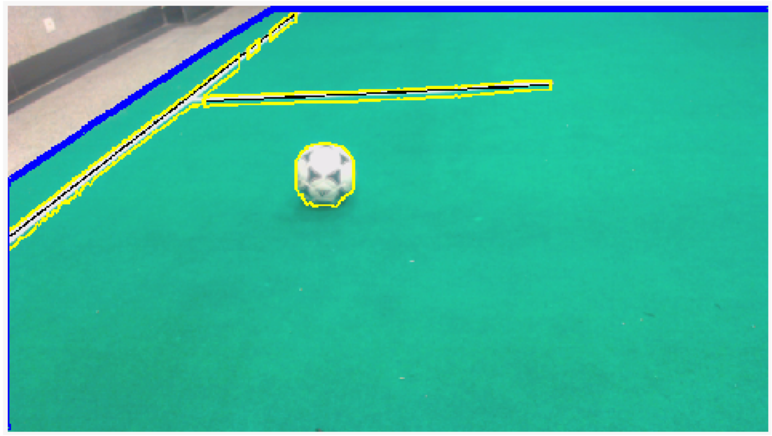

Figure 4: Detected lines and the boundary of the ball.

Finally, we must state that it's our honor to share our research experiences in AUTMan Humanoid robotic team among other researchers and we hope the content will be helpful.

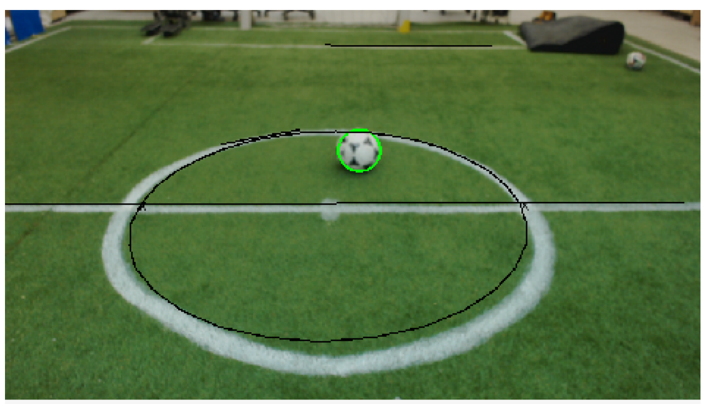

Figure 5: Output of recognition task.

References

[1] Javadi M, Azar SM, Azami S, Shiry S, Ghidary SS, Baltes J. Humanoid Robot Detection using Deep Learning: A Speed-Accuracy Tradeoff, International Robocup Symposium, July 2017.

[2] Rőfer T, Laue T, Műller J, Bartsch M, Batram MJ, Bőckmann A, Bőschen M, Kroker M, Maaß F, Műnder T, Steinbeck M. B-Human team report and code release 2013 (2013), only available online: http://www. b-human. de/downloads/publications/2013. CodeRelease2013. pdf.