Camellia Dragons

Team Report 2017

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January 31, 2018

Chapter 1

Introduction

1.1 About Us

Camellia Dragons was organized in October, 2013 at Aichi Prefectural University (APU), Japan. The team has been participated in the Standard Platform League (SPL) competition for RoboCup Japan Open since 2014. The results were first place in 2014 and 2015, and second place in 2016 and 2017. The team participated in the drop-in player competition and the technical challenges in RoboCup 2015 [1], and participated in the team competition in RoboCup 2016 [2] and 2017 [3]. We awarded the first place of the team competition at challenge shield and also became quarter finalists of penalty kick competition in RoboCup 2017.

1.2 Team Information

Camellia Dragons is a RoboCup soccer SPL team set up at APU. The team consists of two masters students, 17 undergraduate students, and two faculty members; Yo Aizawa (the present team leader), Kenta Hidaka (ex-team leader), Nodoka Mori, Kosei Ohkusu, Kazuho Takahashi, Yoshiyuki Uemura, Mikiya Chiba, Keiji Hayashi, Kazuki Ito, Toshiki Nagami, Yuji Shimizu, Yuji Yamada, Kouki Hosokawa, Shinya Ito, Takashi Kuboya, Goki Ohta, Takuma Tachi, Kazumi Tanabe, Kazuya Tsubokura, Assist. Prof. Dr. Takuo Suzuki, and Prof. Dr. Kunikazu Kobayashi.

Most of them are affiliated with Intelligent Machine Learning laboratory (IML lab) at APU. Currently, we have 20 NAO robots, a half of them are H25 Next Generation (Version 5) and all the rest are H25 Next Generation (Version 4).

1.3 Code Usage

The team used B-Human code release 2013 [4] at RoboCup Japan Open 2014, B-Human code release 2014 [5] at RoboCup Japan Open 2015 and RoboCup 2015, B-Human code release 2015 [6] at RoboCup Japan Open 2016 and RoboCup 2016, and B-Human code release 2016 [7] at RoboCup Japan Open 2017 and RoboCup 2017. We deeply appreciate B-Human for the great contribution to soccer SPL. Toward RoboCup 2018, the team modified B-Human code release 2016 [7] and originally added two main functions: (1) Replaced our realistic ball perception [2, 3] in Cognition module (the details seen in Chapter 2), (2) Added penalty kick behavior in Cognition and Motion modules (the details seen in Chapter 3).

Chapter 2

Ball Recognition

2.1 Background

The official ball has been changed from the orange street hockey ball to the soft foam ball with a black and white soccer ball print since RoboCup 2016.

We developed a method of realistic ball perception in RoboCup 2016. But it contains some problems that a part of the robot may be incorrectly detected as the ball and it may not accurately recognize the ball in an environment with natural lighting. After the competition in RoboCup 2016, we developed a new ball recognition method using cascade classifier [8] with boosting which is one of machine learning techniques as described in RoboCup 2017's TDP [3]. The proposed method could recognize the ball up to 3.2[m] away even under a natural lighting environment. However, the proposed method sometimes erroneously recognized the robot as the ball. It was difficult to recognize the ball when it overlapped over the lines and the robot. Toward RoboCup 2017, we therefore improved the precision by reviewing features and images to be used in learning. As a result, false recognition was decreased in various situations. The revised method could recognize the ball up to a half of the field, i.e. 4.5[m] away.

The proposed ball recognition system was implemented by replacing the realistic ball challenge module of B-Human code release 2015 [6]. With respect to a method to acquire the candidate region of the ball, we employ the BallRegion module in B-Human code release 2016 [7].

2.2 Preliminary Simulation

In order to evaluate the proposed ball recognition method using cascade, we compare three feature quantities of Haar-like, local binary patterns (LBP), and histograms of oriented gradient (HOG).

2.2.1 Problem Setting

As preliminary experiment, we compare the recognition accuracy and the processing speed for the cascade classifier with the above three features. In this simulation, learning is performed using the same image dataset and parameter setting for each feature. The parameter setting is shown in Table 2.1. Using the created cascade classifier, we verify the test accuracy for 100 ball images and calculate the average processing speed per an image.

2.2.2 Simulation Result

The results are shown in Table 2.2. From this result, it is clear that there are many false recognition in LBP and HOG feature quantities and they require much processing time. On the other hand, Haar-like feature quantity has a high recognition rate and it is smaller than the misrecognition rate LBP. And it turns out that the processing time is earlier than the other two. Therefore, it is considered that Haar-like feature quantity is suitable for recognizing the ball.

Table 2.1: Paramater setting

Parameter	Value
Boosting type	Gentle AdaBoost
Image size	16×16
# of stages	14
# of positive images (Indoor) (Outdoor)	700 (490) (210)
# of negative images	300

Table 2.2: Result

Feature quantity	Recognition rate [%]	# of false recognition [pcs]	Processing speed [mspf]
Haar-like	95	44	42.7
LBP	97	197	50.6
HOG	86	5	93.5

2.3 Method

In the proposed method, the cascade classifier is used to recognize the ball. We use OpenCV as an image processing library.

2.3.1 Extracting Ball Area

Detecting a ball using the whole image, it takes too much time to process. Therefore, we extract the region candidates of the ball from the image and apply them to detectors in order to implement real-time processing.

In our TDP for RoboCup 2017 [3], as focusing on the black pentagon of the ball and limiting the search area to it, we propose the real-time ball recognition method for changing lighting conditions. At first, we focus on the black regions on the official ball. After labeling them, we determine the size of circumscribed rectangle (bounding box) for each black region. If black regions are overlapped, we create a new circumscribed rectangle that contains all the overlapped regions. Repeating this process, we expect to get only one rectangular region. However, this method detects a search area in other regions like the robot and takes unnecessary processing time. In addition, it is difficult to adjust the values of parameters.

Therefore, we determine to employ the BallRegion module in B-Human code release 2016 as a method of acquiring the candidate regions of the ball, By using this module, we can acquire areas where it is supposed to have a ball, so we use a classifier to recognize the ball against those area.

2.3.2 Creating Classifier

The cascade classifier are created by boosting using OpenCV. In our TDP for RoboCup 2016 [2], we use LBP as feature quantity but change it to Haar-like feature quantity in RoboCup 2017. Through preliminary simulations, we confirm that Haar-Like feature quantity can be processed faster than LBP one and false recognition to other objects is minimum. It also can be seen that the processing speed of HOG feature amount is slow. Therefore, we create a cascade using Haar-Like feature quantity.

The recognition accuracy greatly depends on training images. Therefore, it is necessary to carefully select images for training. For example, in actual play, it is considered that the ball on the lines of the field and a robot behind the ball. If the system trains without such images, it may be difficult to recognize the ball in the actual situation. Therefore, the image used for learning needs to collect in various situations, and creates a classifier suitable for the actual environment.

2.3.3 Training Image

We prepare training image set that consists of 1,356 and 368 images in an indoor and outdoor environments, respectively and also use the SPQR image dataset [1] which contains 2,917 images. Totally, we prepare 4,661 positive images and 4,207 negative ones for the ball. Our image dataset will be posted on our web site soon.

2.3.4 Recognition Accuracy

Using the cascade classifier, the ball is detected from the ball candidate area. The recognition results in the indoor environment are shown in Figures 2.1 to 2.4. In Figure 2.1, it is possible to stably recognize the ball located 3.0[m] apart. In Figure 2.2, it is shown that our method could recognize the ball placed on the center mark from the edge of the field (4.5[m]). It is also confirmed that our method could recognize the ball placed over the line as seen in Figure 2.4. The recognition result in outdoor environments is shown in Figure 2.4. From this Figure, it is confirmed that it could be recognized even in the outdoor environment.

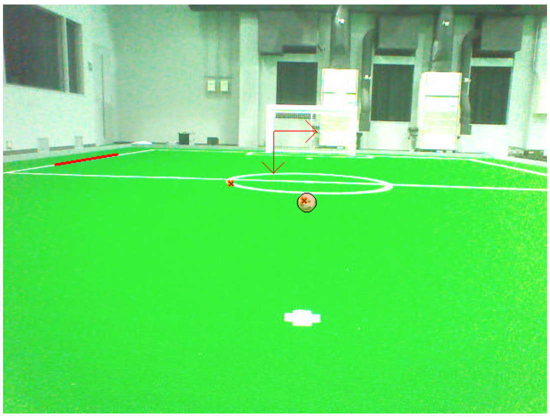

Figure 2.1: Recognition from 3.0[m] away

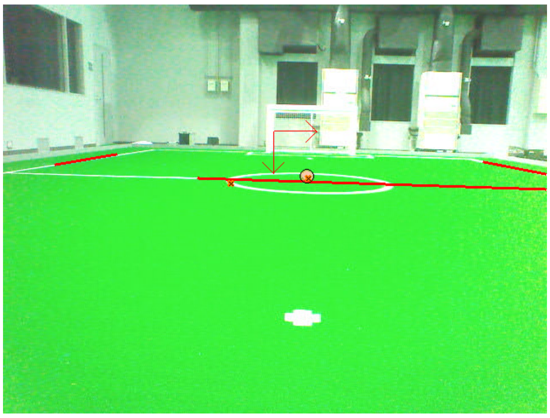

Figure 2.2: Recognition from 4.5[m] away

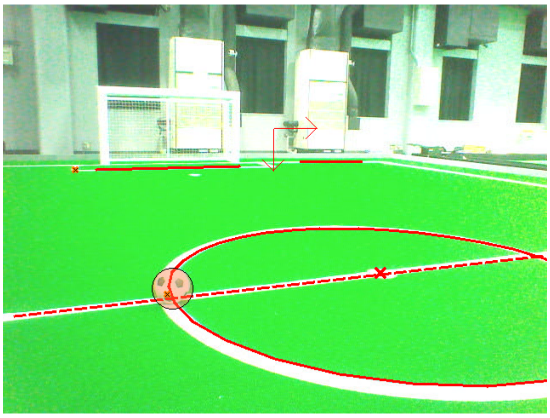

Figure 2.3: Recognition of the ball on the line

Figure 2.4: Recognition in the outdoor environment

[1] http://www.dis.uniroma1.it/ labrococo/?q=node/459

Chapter 3

Penalty Kick

We developed the penalty kick behavior and became quarter finalist of penalty kick competition in RoboCup 2017.

3.1 Goalie

In penalty kick, the goalie needs to be able to quickly judge if the ball is kicked by the kicker. We use the background subtraction method in order to immediately judge if the ball is moving or not. Initially, it recognizes the position of the ball and memorizes the lower end position. Applying the background subtraction method, the kicker does not show up in the background subtraction. As a result, processing time of the background subtraction is reduced. When the goalie recognizes that the ball is moving, it takes a ball saving action.

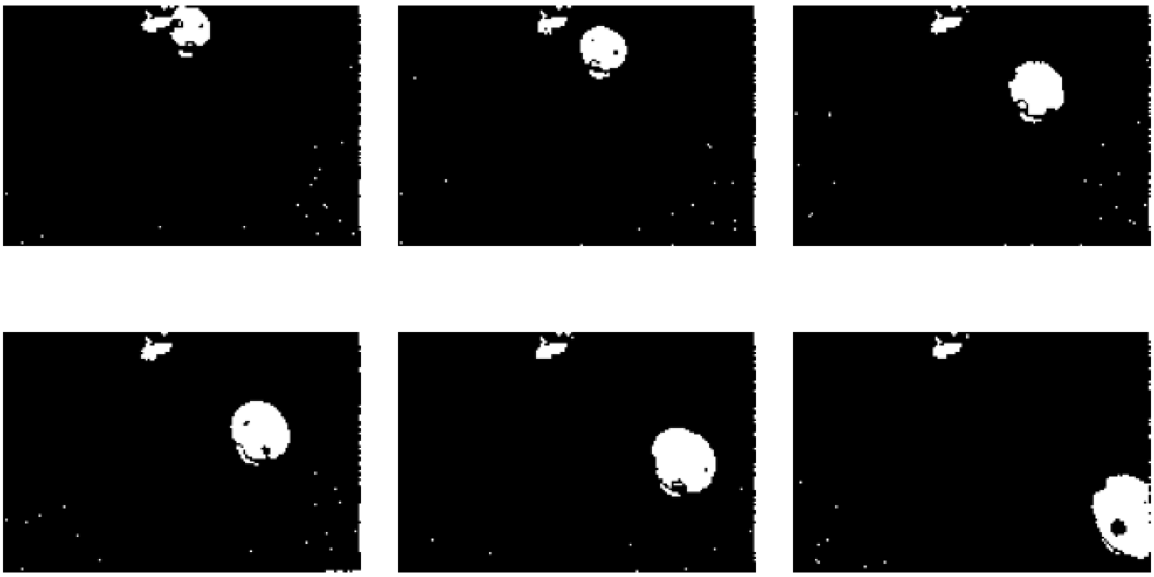

Figure 3.1: Images of background subtraction

3.2 Kicker

The kicker needs to detect the position of the goalie and kick its opposite position. We therefore decide the direction to kick from the position of the goalie and the position of the goal post. When the goalie is standing in the center of the goal, it makes the kick towards the right end of the goal. When the goalie is on left or right side, the kicker makes the kick towards the center of the goal. Since the kicker must not touch the ball before making the kick, it carefully approaches the ball little by little and determines the position to make the kick.

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