Camellia Dragons

Team Description Paper for RoboCup 2017

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1 Introduction

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. The team participated in the SPL drop-in player competition and the SPL technical challenges in RoboCup 2015 [1], and participated in the SPL main competition in RoboCup 2016 [2] and 2017. We are really happy to challenge the SPL main competition for RoboCup 2017 to be held in Nagoya, Japan as a representative team of the host country.

2 Team Information

Camellia Dragons is a SPL team set up at APU. The team consists of two masters students, seven undergraduate students, and two faculty members; Kenta Hidaka (the present team leader), Yoh Aizawa, Kana Futatsuishi, Nodoka Mori, Kosei Ohkusu, Kazuho Takahashi, Yoshiyuki Uemura, Kazuki Ito, Haruki Niwa, Assist. Prof. Dr. Takuo Suzuki, and Assoc. Prof. Dr. Kunikazu Kobayashi. All 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).

3 Code Usage

The team used 2013 B-Human code release [3] at RoboCup Japan Open 2014, 2014 B-Human code release [4] at RoboCup Japan Open 2015 and RoboCup 2015, 2015 B-Human code release [5] at RoboCup Japan Open 2016 and RoboCup 2016, and 2016 B-Human code release [6] at RoboCup Japan Open 2017. We deeply appreciate B-Human for the great contribution to SPL. Toward RoboCup 2017 SPL competition, the team modified 2016 B-Human code release [6] and originally added three main functions: (1) Revised our realistic ball perception [1] in Cognition module (the details seen in Section 5.1), (2) Created a coaching robot function in Cognition module (Section 5.2), (3) Realized collective plays in Motion module (Section 5.3).

4 Past History

The team made a debut at the SPL competition for RoboCup Japan Open 2014 and won first place in the main competition. In RoboCup Japan Open 2015, we participated in the SPL competition for RoboCup Japan Open 2015. Finally, we won first place in the main competition in a row and also went to the top in the technical challenge. In RoboCup Japan Open 2016 and 2017, we awarded second place in the main competition. The team firstly challenged to RoboCup 2015 in Hefei, China and participated in the SPL drop-in player competition and the SPL technical challenges [1]. In RoboCup 2016 in Leipzig, Germany, the team firstly participated in the main competition, which was the first Japanese team to join it [2]. Table 1 summarizes the team's history at RoboCup SPL competitions.

Table 1. Results at the RoboCup competitions

competition	main competition	drop-in player	technical challenge
RoboCup Japan Open 2014	1st (4 teams) Final: Camellia Dragons 2 : 1 Crude Scientist Round Robin #1: Camellia Dragons 0 : 0 JoiTech-SPL Round Robin #2: Camellia Dragons 1 : 1 Crude Scientist Round Robin #3: Camellia Dragons 3 : 0 Taipei Tech	-	4th (4 teams)
RoboCup Japan Open 2015	1st (4 teams) Final: Camellia Dragons 4 : 0 JoiTech-SPL Round Robin #1: Camellia Dragons 1 : 0 IRUF Round Robin #2: Camellia Dragons 3 : 1 Crude Scientist Round Robin #3: Camellia Dragons 2 : 3 JoiTech-SPL	-	1st (4 teams)
RoboCup 2015	Not qualified	25 (27 teams)	11th (23 teams)
RoboCup Japan Open 2016	2nd (4 teams) Final: Camellia Dragons 0 : 2 JoiTech-SPL Round Robin #1: Camellia Dragons 0 : 0 IRUF Round Robin #2: Camellia Dragons 0 : 0 JoiTech-SPL Round Robin #3: Camellia Dragons 0 : 0 rUNSWift	-	-
RoboCup 2016	1st round Play-in Round: Camellia Dragons 0(0) : 0(2) SPQR 1st Round Robin #1: Camellia Dragons 1 : 1 RoboEireann 1st Round Robin #2: Camellia Dragons 0 : 0 Northern Bites 1st Round Robin #3: Camellia Dragons 0 : 1 DAInamite	25 (26 teams)	-
RoboCup Japan Open 2017	2nd (3 teams) Final: Camellia Dragons 1 : 3 JoiTech-SPL Round Robin #1: Camellia Dragons 1 : 1 IRUF Round Robin #2: Camellia Dragons 1 : 0 JoiTech-SPL	-	-

5 Impact

The team prepares to participate the SPL team competition. We believe that the team has positive impact on development of SPL if participating in RoboCup. Actually, in current SPL, it is hardly seen advanced cooperative play involved two or more robots such as one two pass. Our IML lab has published a lot of papers regarding cooperative behavior in multi-agent system [7–13] in which we use various machine learning techniques [14–17]. We therefore contribute SPL to realize human-like cooperative soccer play involving multi robots. After participating in RoboCup Japan Open 2014, the student members get a chance to learn various fields such as image processing and communication, and then gain broad knowledge from robotics to artificial intelligence. The team make a SPL demo at a lot of robot events in our community to focus spotlight on RoboCup and also APU.

Toward RoboCup 2017 SPL competition, the main research contributions to SPL are as follows: (1) Proposed a recognition method to precisely perceive the realistic ball (Section 5.1), (2) Proposed a self-localization method employing a coaching robot (Section 5.2), (3) Proposed a cooperative method to realize collective plays (Section 5.3).

5.1 Realistic Ball Perception

The official ball was changed from the orange street hockey ball to the soft foam ball with a black and white soccer ball print in 2016. We developed a realistic ball perception in RoboCup 2016 [2]. But it contains the 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. In this TDP, we proposes a new realistic ball perception method using image feature amount. Generally, most methods using image feature amount requires huge amount of computational cost. We therefore focus on the black hexagon on the ball and limit the search area, and then propose a real-time and robust method for change in environment.

Fig. 1. An example of ball perception under the shadow of sunlight in an outdoor environment.

Fig. 2. An example of ball perception under the sunlight exposure in an outdoor environment.

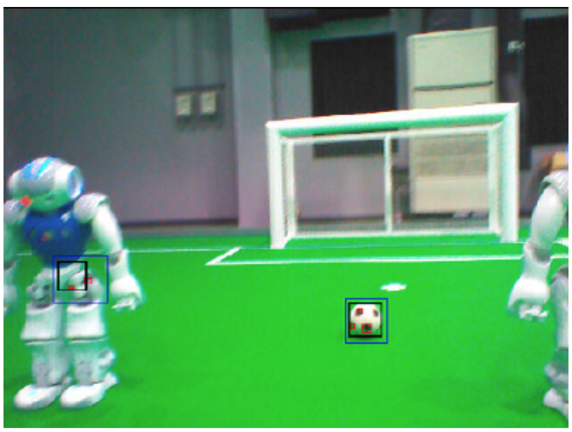

Fig. 3. An example of ball perception without sunlight in an indoor environment.

At first, we focus attention on the black regions on the SPL 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. After that, we apply local binary pattern (LBP) [18] to the region. The LBP captures features by brightness distribution and is robust against brightness changes. We prepared training image set that consists of 784 and 536 images in an indoor and outdoor environments, respectively and used the SPQR team NAO image dataset [1] that contains 209 positive and 500 negative images. After learning using these images, we calculate the ratio of black and white regions by two thresholds using color information in a L*a*b* color space for the rectangular region.

Through real robot experiments, it is verified that the proposed method can correctly recognize the ball in an outdoor environment. The black rectangles in Figs.1 and 2 are recognized to be a ball inside. Figures 1 and 2 show the results under the shadow of sunlight and the sunlight exposure in an outdoor experiment, respectively. The proposed method can recognize balls within approximately 3.2[m] and extremely reduce the false recognition. It can also process for one rectangle at about 10[ms] on NAO robots. It can suppress a false detection for a bleary image as shown in Fig.3 by the ratio of black and white regions.

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

Fig. 4. A perspective image from a coaching robot.

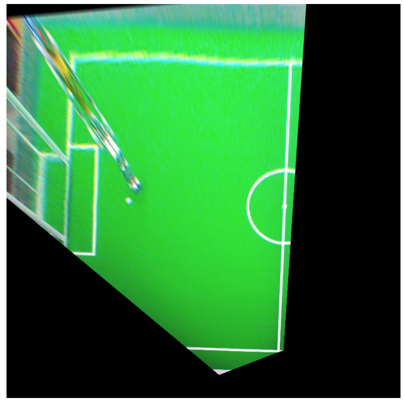

Fig. 5. A true perspective image by the homography transform.

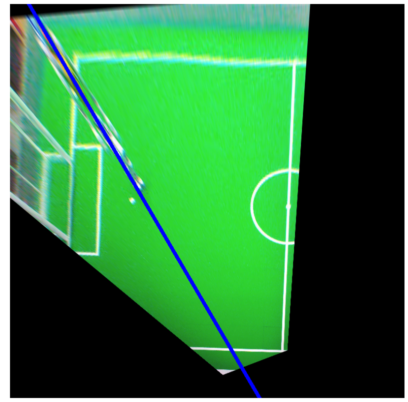

Fig. 6. An estimated line by the simple linear regression analysis.

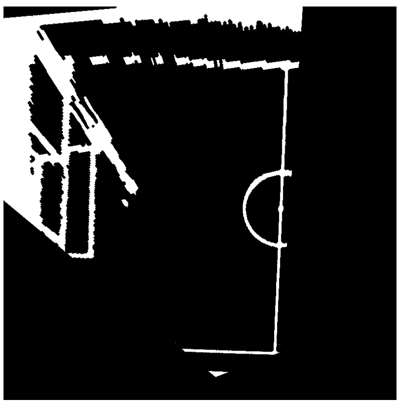

Fig. 7. A binary image of the player robot.

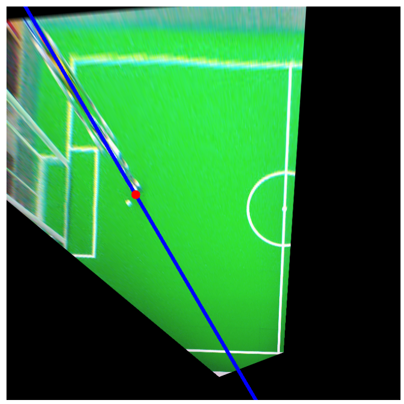

Fig. 8. An estimated foot position (red dot).

5.2 Coaching Robot's Role

Officially, a coaching robot was introduced in 2014. Since then, any team has not challenged to utilize the coaching robot. We are really motivated to utilize the coaching robot and discussing how to realize it. At the next year's RoboCup competition, we are going to present an approach to correct the estimated self-position by utilizing the coaching robot.

We employ unscented particle filter (UPF) for self-localization of robots provided by B-Human code release [5]. The UPF uses the information of lines, penalty marks and goals on the SPL field as landmarks. When a robot cannot recognize such landmarks exactly, the estimation precision of the self-localization decreases dramatically because the particles of UPF will spread. In addition, as the color of goals was changed from yellow to white in 2015, it is difficult to recognize goals and then precisely estimate the self-localization of robots.

We therefore motivated to introduce a coaching robot in order to assist a player robot with estimating its self-localization. The coaching robot observes the player robot on the SPL field with its own vision, calculates the position coordinate, and then sends it to the player robot. The player robot can use the global vision of the coaching robot as well as its own local vision. It is therefore expected that the player robot will improve its self-localization ability.

At first, the coaching robot gets a perspective image as shown in Fig.4. Then we transform it to a true perspective image using homography transform (see Fig.5). Since the homography transform requires more than four coordinates on an image, we use the corners of the field and the penalty areas, the penalty crosses, the intersections of the side-lines and the center line, and the center mark. as the candidates of four coordinates. To improve the precision of the homography transform, we allocate the coaching robot so as to view candidates as many as possible. After that, we extract a region of the own team's jersey, it is certain that the player robot will be on the line calculated by simple linear regression analysis (see Fig.6).

Finally, the foot position of the player robot is estimated as the bottom point of non-green regions on the line (Fig.6). We transform the color space of the perspective image into L*a*b* to detect the color of the field. L* stands for lightness and a* and b* are hue and saturation, respectively. The color approaches red as the value of a* becomes high and green as it becomes low, and yellow as the value of b* becomes high and blue as it becomes low. We binarize the image of a* by Otsu's thresholding method. As applying the homography transform to the image, the true perspective image is shown in Fig.7. The estimated foot position is illustrated in Fig.8 as a red dot. Actually, the avarage error between the estimated foot position and the actual measured value was 126[mm].

5.3 Collective Plays

Collective plays are still not very common at the SPL main competition. Most of teams are just aiming to get scores. However we all should try to be human-like in order to achieve our dream. Team plays are really important at the real human soccer. To accomplish collective team plays, we introduce Player Priority.

Player Priority A method to acquire cooperative action using a reinforcement learning system is proposed by Tsubakimoto et al. [12, 13]. Based on this method, we proposed a new method to play soccer cooperatively. The proposed method shows which player is priority against the ball. This is helpful to accomplish collective plays.

All the players calculate player priority of all the teammates including itself. Three variables(d, *theta* and v_k) are required to calculate a player priority PP_k for a robot k. Now, d is a distance between a ball and the robot, θ is an angle between an opponent goal and the robot as shown in Fig.9, and v_k is a validity of self-localization. The validity is calculated by unscented Kalman filter in B-Human's self-localization system. It takes a real value within $[0, 1]$ and the best is 1. Player priority is calculated by Eq.(1).

$$PP_k = v_k(\alpha\, Dir_{g,k} + \beta\, Dis_{b,k})/(\alpha + \beta)), \tag{1}$$
$$\begin{cases} Dir_{g,k} = (\cos\theta + 1)/2, \\ Dis_{b,k} = d^{-1}, \end{cases}$$

where α and β are both weighting parameters and normally set to 1.0. P_k takes a normalized value within $[0, 1]$. The distance might be more important than the direction in SPL. Both $Dir_{g,k}$ and $Dis_{g,k}$ take a normalized value within $[0, 1]$. Every robots calculate player priority to all the teammates and itself at all times. Then, robots can play soccer cooperatively, e.g. a robot which is the highest priority walks to a ball and another robot which is the second priority receives a ball passed by the first robot. Furthermore, player priority is useful to predict opponent strategy by calculating opponent Player Priority.

Dynamic Roles We develop three roles and switch them all the time by comparing their player priority during a game. So that, players are able to switch roles dynamically and act cooperatively. Therefore, we don't need to set roles to players before a game. It comes more flexible because of this system. Details of these roles are following subsections.

1. Striker
   A striker simply goes to the ball and kick it to the opponent's goal. A striker is always the highest priority and only one on the field.

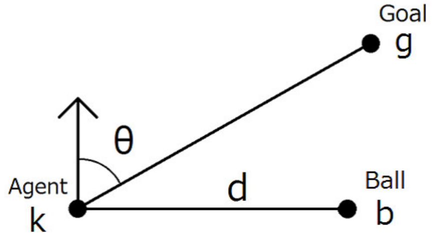

Fig. 9. Positional relation between an agent, a ball and opponent goal.

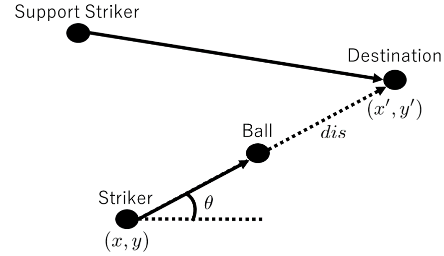

Fig. 10. Positional relation between an agent, a ball and opponent goal.

2. Support Striker

   A support striker assists a striker. This role is made to achieve collective offensive plays. A support striker always goes to the position where the ball will be kicked to by a striker as shown in Fig.10. We call the position destination. Here, coordinate(x, y) shows a position of a striker, coordinate(x', y') shows the destination, dis is a constant distance between a ball and the destination, θ is an angle of a striker. A support striker calculates the destination using pose of a striker and the ball by Eq.(2).

$$x' = x + dis \cdot cos\theta,$$
$$y' = y + dis \cdot sin\theta, \tag{2}$$

   A support striker is always the second highest priority and only one on the field.
3. Defender

   Defenders simply wait for the ball at their position. They are lower priority compared to a striker and a support striker. Defenders are usually two from five players.

6 Conclusion

We have proposed the three new methods toward RoboCup 2017. (1) Revised our realistic ball perception in RoboCup 2016. (2) Created a coaching robot function. (3) Realized collective plays. Through the main competition in RoboCup 2017. We evaluate the performance of the proposed methods.

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