Camellia Dragons

Team Report 2017

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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 2017, the team modified B-Human code release 2016 [7] and originally added five major functions: (1) collective plays [1, 2, 3] in Motion module (the details seen in Chapter 2), (2) a realistic ball perception method [2, 3] in Cognition module (the details seen in Chapter 3), (3) player's roles for midfielder, defender and goalie, and an original striker's role [1, 2] in BehaviorControl module (the details seen in Chapter 4), (4) a computational cost reduction method of self-localization system [2] in Cognition module (the details seen in Chapter 5), (5) penalty kick behavior in Cognition and Motion modules (the details seen in Chapter 6).

1.4 Code and Dataset Release

Toward RoboCup 2018, we published our code for realistic ball perception and penalty kick motions. You can reach it at the open-access site:
`https://github.com/CamelliaDragons/CamelliaDragonsCodeRelease`.

We also published our image dataset for public use. You can obtain it at Camellia Dragons' team site:
`http://www.ist.aichi-pu.ac.jp/lab/robocup-spl/en/publications.html`.

Chapter 2

Collective Plays

Collective plays are important at the real human soccer. Most of the scoring comes from team play in human soccer. Therefore team plays are really important at the real human soccer. We all should try to be human-like in order to achieve our dream. To accomplish collective team plays, we introduce player priority.

We proposed a method to acquire cooperative action using a reinforcement learning system [11, 12]. 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.2.1, 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.(2.1).

$$PP_k = v_k(\alpha\, Dir_{g,k} + \beta\, Dis_{b,k})/(\alpha + \beta)), \tag{2.1}$$
$$\begin{cases} Dir_{g,k} = (\cos\theta + 1)/2, \\ Dis_{b,k} = d^{-1}, \end{cases}$$

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.

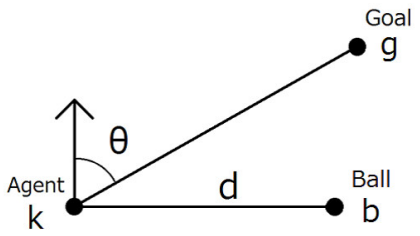

Figure 2.1: Positional relation between an agent, a ball and opponent goal.

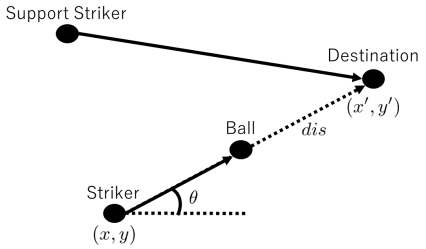

Figure 2.2: Positional relation between an agent, a ball and opponent goal.

Chapter 3

Ball Recognition

3.1 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].

3.2 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).

3.2.1 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 3.1. Using the created cascade classifier, we verify the test accuracy for 100 ball images and calculate the average processing speed per an image.

3.2.2 Simulation Result

The results are shown in Table 3.2. 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 3.1: Paramater setting

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

Table 3.2: 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

3.3 Method

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

3.3.1 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.

3.3.2 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.

3.3.3 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.

3.3.4 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 3.1 to 3.3. In Figure 3.1, it is possible to stably recognize the ball located 3.0[m] apart. In Figure 3.2, 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 3.3. The recognition result in outdoor environments is shown in Figure 3.4. From this Figure, it is confirmed that it could be recognized even in the outdoor environment.

Figure 3.1: Recognition from 3.0[m] away

Figure 3.2: Recognition from 4.5[m] away

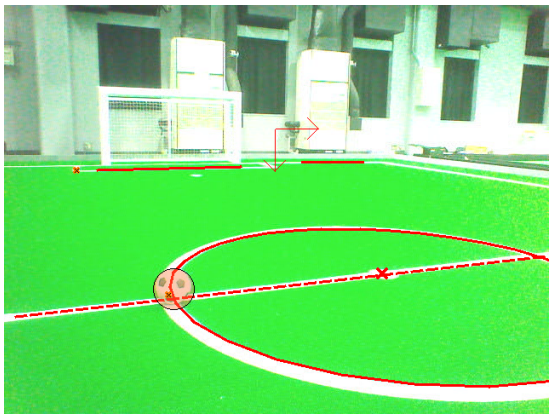

Figure 3.3: Recognition of the ball on the line

Figure 3.4: Recognition in the outdoor environment

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

Chapter 4

Player's Role

We prepared three new roles, i.e. striker, midfielder, defender, and goalie and revised the role of the striker in B-Human's BehaviorControl module [5] in order to clarify the tasks to fulfill of five robots and make robots act for the team [1] .

Striker The basic role is to score a goal. The home position is near center circle in the opponent field as shown in Fig.4.1. It can only move inside the opponent field. It should wait until a ball enters in the own area. When it cannot find a ball, it receives the positional information on the ball from other robots through team communication.

Figure 4.1: Home positions for five robots.

Midfielder The basic role is to play in all field area and its home position is near the center circle (See Fig.4.1). Mainly, it supports striker by kicking a ball to the opponent field and chasing a ball in the near center circle. It may score a goal.

Defender The basic role is to kick a ball against the opponent field. It can only act in own field. It always receives the positional information of the ball from other robots by team communication. So it turns to the direction of the ball. When a distance which between current own position and the ball becomes near, it approaches a ball to kick it. We prepare two defenders in right side and left side of own field.

Goalie The basic role is to defend a goal. Its home position is within own penalty area (See Fig.4.1). When it cannot find a ball, it keeps looking for a ball as shaking own head. After it can find the ball, when the distance between the current position and the ball is far, it moves sideways to the ball. When the distance is near, it goes out of the own penalty area and approach the ball to kick it.

For each role, we define a fixed area for each robot. This represents a home position. Figure 4.1 shows five centers of home positions corresponding to five robots.

Chapter 5

Computational Cost Reduction of UPF

5.1 Background

In the SPL competition, according to the recent rule changes such as white-colored goals and a realistic ball, robots have heavy computation process to cope with these tasks. We therefore reduce the computational cost in the whole system. To begin with, we focus on the self-localization and try to reduce its computational cost. We now use the unscented particle filter (UPF) to estimate self-localization of a robot [9]. Originally, the number of particles in UPF is determined in advance and fixed during processing. To ensure adequate estimation accuracy, we have to prepare a large enough number of particles. We are therefore able to reduce the computational cost by adjusting the number of particles according to the situation.

We propose an adaptive method to adjust the number of particles in UPF using a weight of particle and a variance of the distances between the centroid of particles which have a weight larger than a threshold and each particle [2]. The details are referred to [10].

5.2 Method

We propose an automatic adjustment method of the number of particles in UKF to reduce the computational cost. The proposed method realizes adjusting the number of particles by two steps, i.e. reset step and increase or decrease step as shown in Figure 5.1.

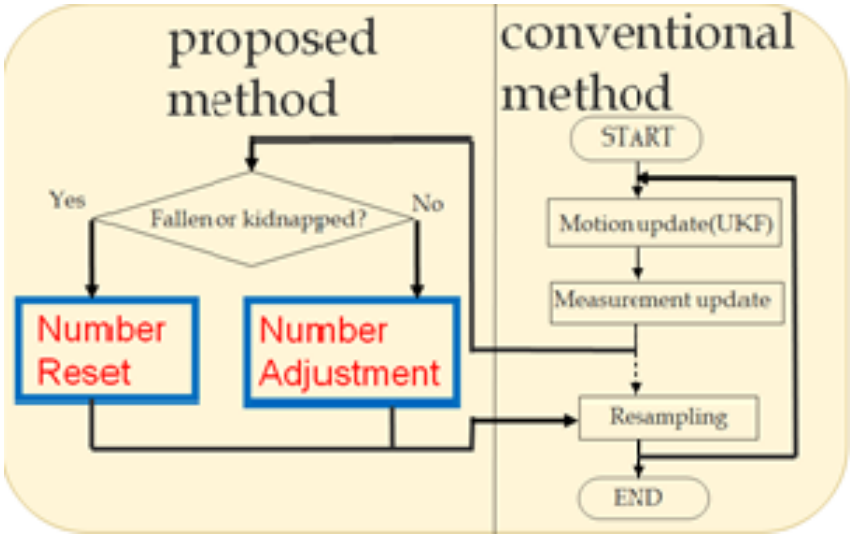

Figure 5.1: The proposed algorithm for adapting the number of particles in UPF.

5.2.1 Reset Step

The reset step will be applied to increase the number of particles when robot is fallen or kidnapped. In RoboCup SPL, since there are so many such cases, a fallen or kidnapped robot must recover from disordered states. We therefore have to increase the number of particles to improve self-localization.

5.2.2 Increase or Decrease Step

In the increase or decrease step, the number of particles can be changed according to the estimation accuracy of self-localization. The detailed algorithm is illustrated in Algorithm 1. Let $X = x_1, x_2, ..., x_N, Y = y_1, y_2, ..., y_n$and X_{new} be sets. σ_n is the standard deviation of the particles with a weight more than α. e_1 and e_2 are any positive real values and used in order to adjust the size of σ_n at time n.

The proposed algorithm will reduce the number of particles if the situation as shown in Figure 5.2.In this figure, the white and black circles correspond to the particles with weights less than α and more than or equal to α, respectively and the yellow circle refers to the centroid of the black ones. If all the white circles are within the circle with radius $e_1\sigma_n$ and centered at the centroid of the black ones, i.e. the yellow circle, we can reduce the number of particles. On the other hand, if any of the white circles is beyond the circle with radius $e_2\sigma_n$, we cannot reduce any particles as shown in Figure 5.3. If all the white circles are within the circle with radius $e_2\sigma_n$ and centered at the centroid of the black ones, we fix the number of particles.

Algorithm 1 Increase or Decrease Step

```
for i = 1 to N do
    if α ≤ weight(x_i) then
        X_new = X_new + x_i
    end if
end for
if |X_new| ≠ 0 then
    if N = |X_new| then
        Y = X_new
        e_1 = parmeter1
        e_2 = parmeter2
    else
        Y = X − X_new
        e_1 = parmeter3
        e_2 = parmeter4
    end if
    μ = E[X_new]
    σ^2 = V[X_new]
    for c = 1 to |Y| do
        if μ − e_1σ < y_c < μ + e_1σ then
            if c = |Y| and N ≠ N_min then
                X = X − min(weight(Y))
                N = N-1
            end if
        else if μ − e_2σ < y_c < μ + e_2σ then
            if c = |Y| then
                break
            end if
        else
            if N = N_max then
                break
            else
                N = N + 1
                break
            end if
        end if
    end for
end if
```

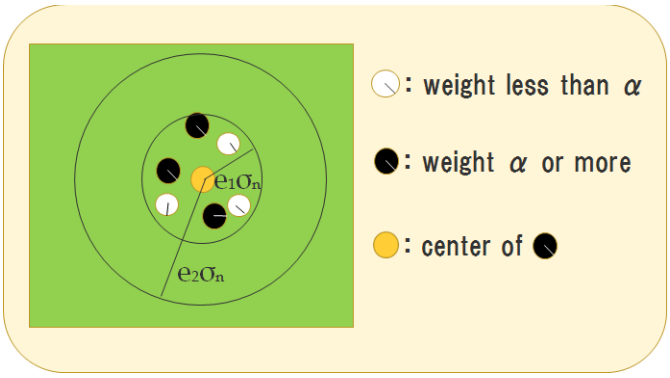

Figure 5.2: An example of deleting a particle.

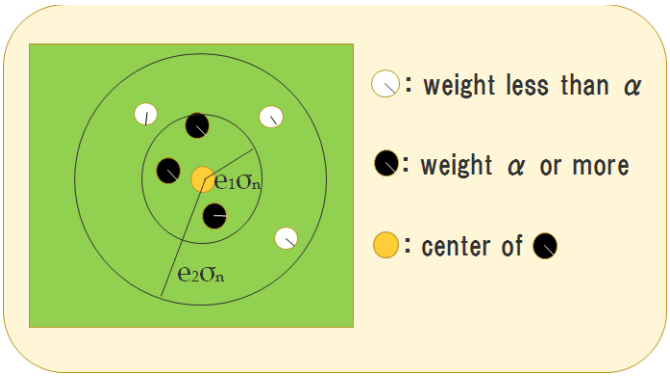

Figure 5.3: An example of adding a particle.

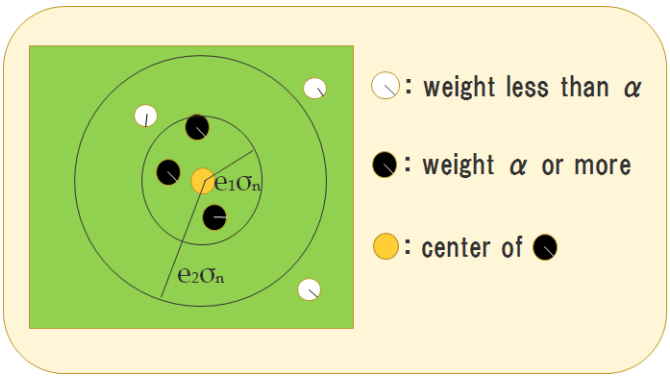

Figure 5.4: An exapmle of fixing the number of particles.

5.3 Computer Simulation

In this section, we show the validity of the proposed method through some computer simulations using SimRobot simulator [5]. Assume that the maximum number of particles is 16, i.e. $N_max = 16$ as the same with the conventional method [5].The values of parameters are set as follows: $N_min = 4$, $parameter1 = 1$, $parameter2 = 2$, $parameter3 = 2$, $parameter4 = 3$, $and\alpha = 0.7$.

Figure 5.5 illustrates the difference between the centroid of particles and true position as the number of cycles. The estimation accuracy of the self-localization using the proposed method is able to maintain the same level as the conventional method. However, the computational results confirm that the self-localization error and the number of particles is not proportional. The number of cycles for processing

the self-localization was measured for 10 seconds. That for the conventional method and the proposed method are 48,340 and 43,880 times, respectively. As a result, the computational efficiency was improved by about 10 percent.

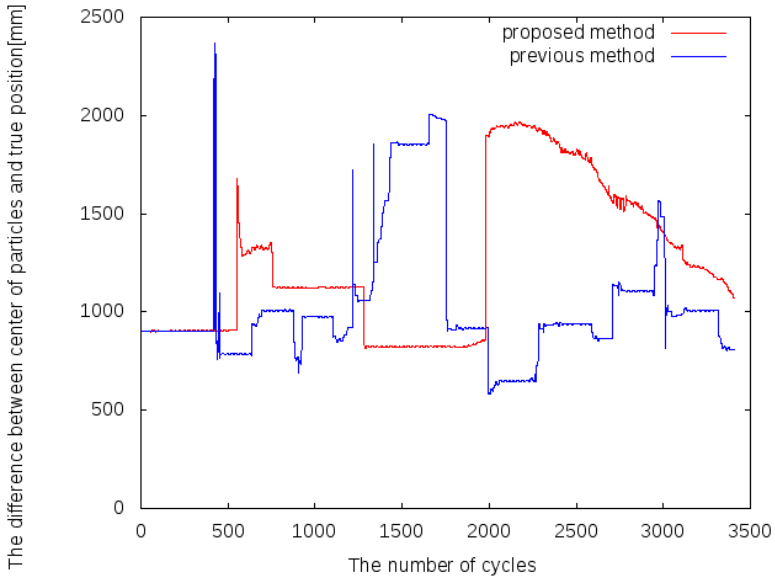

Figure 5.5: Transition of the difference between the centroid of particles and true position.

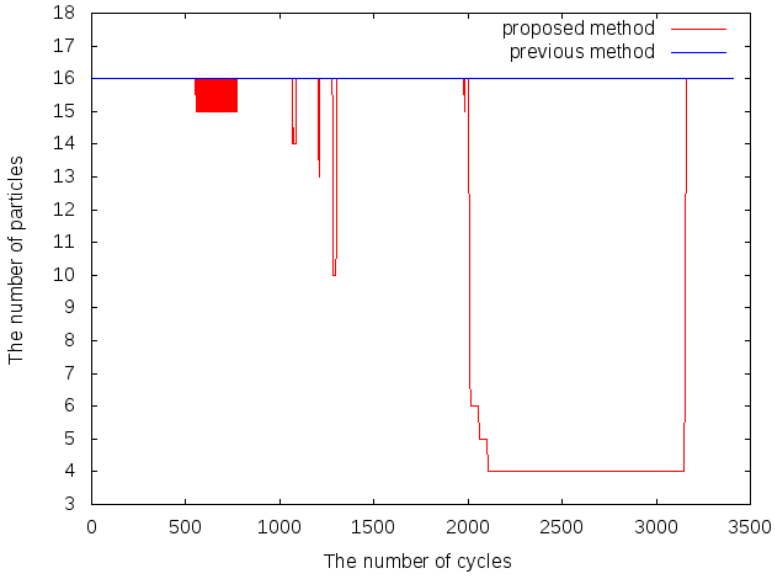

Figure 5.6: Transition of the number of particles.

Chapter 6

Penalty Kick

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

6.1 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.

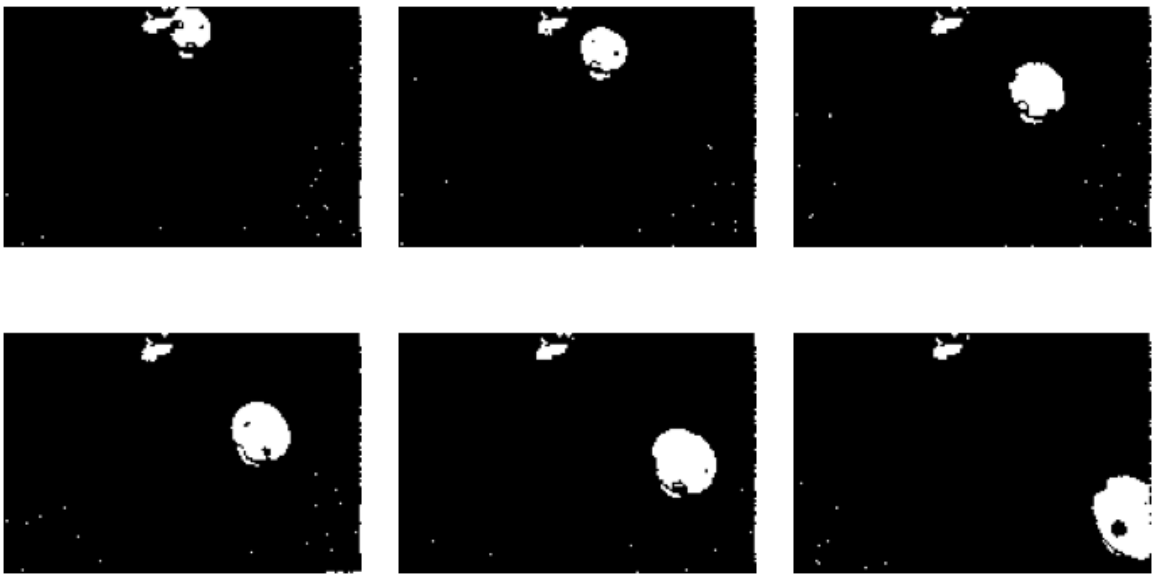

Figure 6.1: Images of background subtraction

6.2 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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