Camellia Dragons

Team Description Paper for RoboCup 2018

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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, 2015 and 2018, and second place in 2016 and 2017. The team participated in the SPL drop-in player competition and the SPL technical challenges in RoboCup 2015 [1], and the SPL main competition in RoboCup 2016 [2], 2017[3] and 2018[4]. We are really motivative to challenge the SPL main competition for RoboCup 2019 to be held in Sydney, Australia.

2 Team Information

Camellia Dragons is a SPL team set up at APU. The team consists of four masters students, sixteen undergraduate students, and a faculty member; Kazuho Takahashi (the present team leader), Kosei Ohkusu, Nodoka Mori, Keiji Hayashi, Mikiya Chiba, Toshiki Nagami, Yuji Yamada, Atsuno Yamaguchi, Natsuki Kato, Masaya Tamai, Takaya Shimizu, Tomoki Tsukamoto, Kazuya Tsubokura, Kouki Hosokawa, Takuma Tachi, Takashi Kuboya, Akihisa Sanae, and Prof. Dr. Kunikazu Kobayashi. All of them are affiliated with School of to Infomation Science and Technology, and most of them are affiliated with Intelligent Machine Learning laboratory (IML lab) at APU. Currently, we have 10 NAO robots, all of them are H25 Next Generation (Version 5). We will obtain 8 NAO robots (Version 6) at the end of February.

3 Code Usage

The team used 2013 B-Human code release [5] at RoboCup Japan Open 2014, 2014 B-Human code release [6] at RoboCup Japan Open 2015 and RoboCup 2015, 2015 B-Human code release [7] at RoboCup Japan Open 2016 and RoboCup 2016, 2016 B-Human code release [8] at RoboCup Japan Open 2017 and RoboCup 2017， 2017 B-Human code release [9] at RoboCup Japan Open 2018 and RoboCup 2018. We deeply appreciate B-Human for the great contribution to SPL.

Toward RoboCup 2019 SPL competition,the team modified 2017 B-Human code release [9]. The changes are shown below:

- In Cognition modules, CascadeBallPerceptor replaced B-Human's module BallPerceptor.
- BallPerceptor on PK. It took a different approach from CascadeBallPerceptor.
- In SelfLocator module, We newly added the method to detect and modify the inversion of self located position (Section 5.3).
- The new module for collective plays was added in Behavior modules (Section 5.4).

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. In RoboCup Japan Open 2018, we awarded first 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. In RoboCup 2017 in Nagoya, Japan, we awarded first place in Challenge Shield and advanced quarter final in Penaly Shootout Competition. In RoboCup 2018 in Motoreal, Canada, we awarded 3rd place in Challenge Shield and advanced quarter final in Penalty Kick Competition.

All our results in the above official games are shown in Table 1.

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 [10–16] in which we use various machine learning techniques [17–20]. 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, communication and self localization, and then gain broad knowledge from robotics to artificial intelligence. The team make SPL demos at a lot of robot events in our community to focus spotlight on RoboCup and also APU.

Toward RoboCup 2019 SPL competition, the main research contributions to SPL are as follows:

- Proposed a ball recognition method using the cascade classifier (Section 5.1).
- Proposed a method to judge which side goalie should protect on PK (Section 5.2).
- Proposed a self-localization method to modify the inversion of self located position (Section 5.3).
- Proposed a cooperative method to realize collective plays (Section 5.4).

We will develop out system to be fully compatible with NAO version 6 for 2019 competition.

5.1 The ball recognition method using the cascade classifier

This method is implemented by replacing B-Human's cognitive module. It's the same module that was replaced by our team in 2018[4] but there are some improvements.

When we were using the proposed module in our team report 2018[4], the process after the cascade classifier is B-Human's one. It judges whether proposed balls is in th field and etc. In this new method, we exclude it. Because that process sometimes excludes correctly recognized ball in proposed balls. At present there is no increase in misrecognition. This is because the recognition accuracy by the cascade classifier is high.

5.2 The method to judge which side goalie should protect on PK

In the case of PK, we use a different recognition method[4] during the game. The advantage of this technique is that it is possible to judge the movement of the ball faster and more stably than the recognition method used in the game.

Toward RoboCup 2019 SPL competition, we create new motion to defend shooting to corners of the goal, and along with that, updated the proposed method in our team report 2018[4]. Measure the angle of the penalty mark at the upper end of the screen presumed to have and the ball after it moves, and select the motion according to the angle.

It is shown in Fig.1. θ is the angle to the ball after it moves.When θ is larger than X, the goalie use new motion.

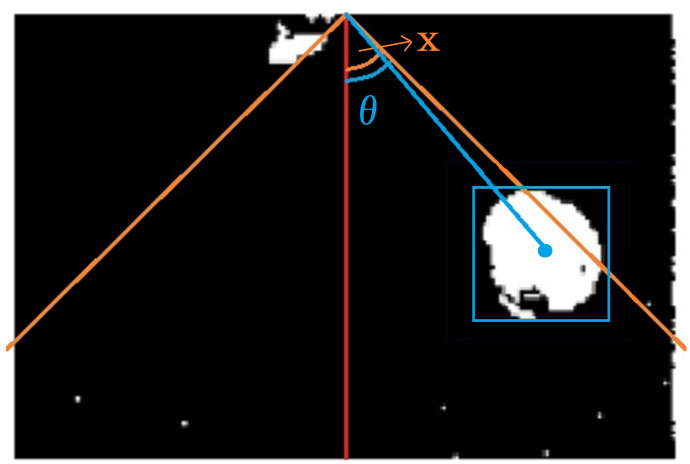

Fig. 1. Calculation process to modify the inversion.

5.3 Detection and modification of the inversion of self located position.

We employ unscented particle filter (UPF) for self-localization of robots provided by B-Human code release[9]. The UPF uses the information of lines, penalty marks and goals on the SPL field, etc. as landmarks.

However, the self located pose inverts sometimes because the SPL field is line symmetry. The inversion of self located position cannot be detected by using the information of field landmarks. In RoboCup Japan Open 2018, we recognize that the inversion was observed in 3 games out of 5 games. It was observed twice in a game out of 3 games. And In RoboCup Montreal, the inversion occurred 3 games out of 9 games. It was observed 3 times in a game out of 3 games.

We therefore propose a method to detect and modify the inversion of self located position. It's the new method for RoboCup 2019.

The first phase is detection of the inversion of self located position. When the following two conditions are satisfied, it's judged the robot is inverted. The first is three more robots are detecting the ball. The second is that the ball recognized by oneself has a distance of 1000mm to all balls what other robots look. We exclude the situation all balls has difficult position by misrecognition because it's rare case.

The second phase is modification of the inversion. If the inversion is detected, set particles based on the following calculation result.

The calculation process is shown below.Figure 2 illustrated the process. "()" in the sentence corresponds to the symbol in Fig.2. The first step is creating circles. The circle of ball is created by using the ball position (TB) integrated all balls estimated by teammates and the distance (db) between oneself (Blue triangle) and the ball position (SB) estimated by oneself. Circles of teammates is created by using teammates position (TM1 3) and the distance (d) from oneself (Blue triangle) to one of teammates (STM1) recognized by oneself.

The second step is calculating poses. Intersection points of these circles is collect position but it's just point not pose. Then we calculate rotation and get pose (Gray triangle).

The third step is selecting a pose. The function calculate difference between relative coordinates of teammate from these poses and relative coordinates of teammate from oneself. The calculation function return pose (Red triangle) that made smallest difference.

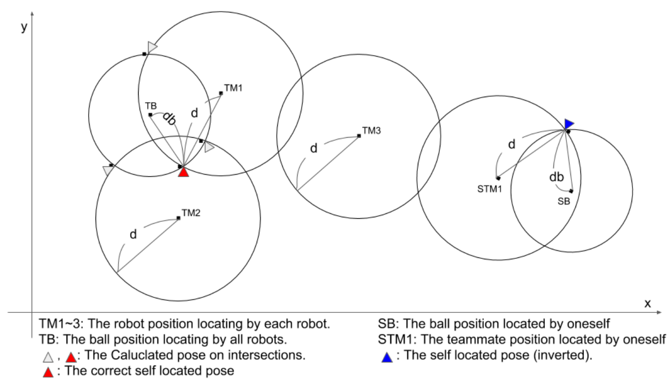

Fig. 2. Calculation process to modify the inversion.

It's the way to detect the inversion and set particle to modify the inversion.

In simulation, this method works well. We are how evaluating in real environment.

5.4 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. [15, 16]. 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. With this method, all the players calculate player priority of all the teammates including itself. Four variables(d, θ_b, θ_g 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_b is an angle between the walking direction and the ball, θ_g is an angle between an opponent goal and the ball as shown in Fig.3, 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).

$$PP_k = v_k(\alpha\, Dis_{b,k} + \beta\, Dir_{b,k} + \gamma\, Dir_{g,k})/(\alpha + \beta + \gamma)), \tag{1}$$

$$\begin{cases} Dis_{b,k} = d^{-1}, \\ Dir_{b,k} = (\cos\theta_b + 1)/2, \\ Dir_{g,k} = (\cos\theta_g + 1)/2, \end{cases}$$

Where α, β and γ are 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. $Dis_{b,k}$, $Dir_{b,k}$ and $Dir_{g,k}$ 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 with the highest priority walks to a ball and

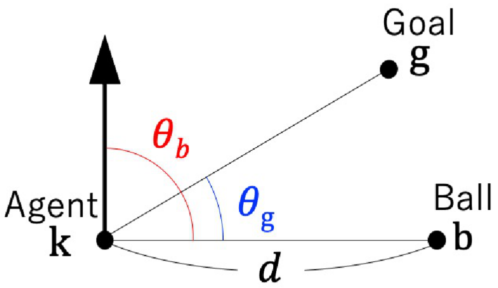

Fig. 3. Positional relation between an agent, a ball and opponent goal.

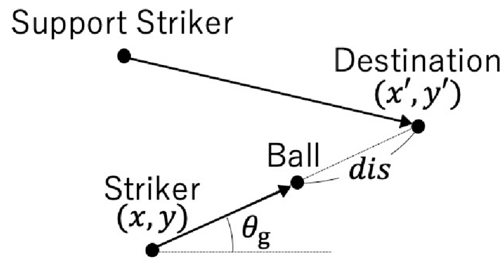

Fig. 4. Positional relation between an agent, a ball and opponent goal.

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.

We proposed the first system in 2016 [3]. This method calculates from the distance between the player and a ball and an angle between the walking direction and an opponent goal. But we think the player with a smaller angle between an opponent goal and the a ball should head to a ball than the player with a smaller angle between the walking direction and an opponent goal in Fig.5. In addition, we also consider the angle between the walking direction and a ball because there is the possibility of the optimal player is not selected with only an angle between an opponent goal and a ball in Fig.6. As a result, the player can head to a ball more efficiently than before.

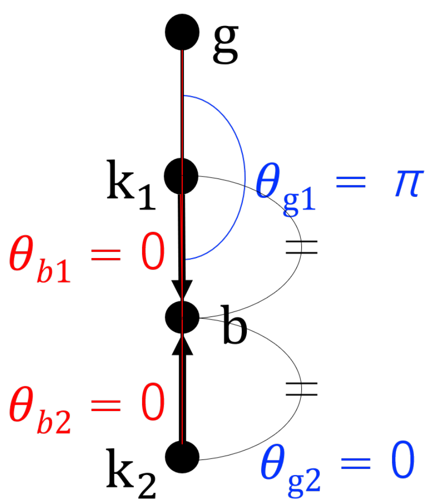

Fig. 5. Reason to consider an angle between an opponent goal and a ball.

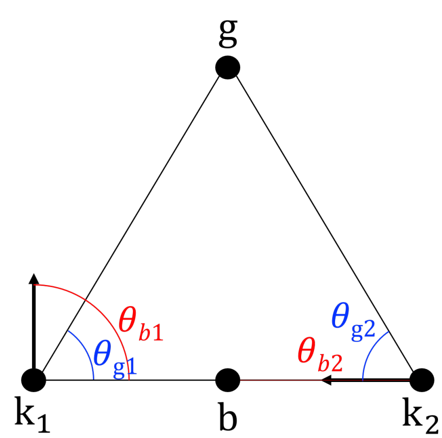

Fig. 6. Reason to consider an angle between the walking direction and a ball.

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 describes as follows.

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.
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 by a striker as shown in Fig.4.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_g is an angle of a striker. A support striker calculates the destination using pose of a striker and the ball by Eq.(2).

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

   A support striker has 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 players.

6 Conclusion

We have proposed four new methods toward RoboCup 2019.

- Improvement of our ball perceptor module.
- The method to judge which side goalie should protect in our ball perceptor module on PK.
- Detection and modification of the inversion of self located position.
- Improvement of our collective plays.

Through the main competition in RoboCup 2019, we evaluate the performance of the proposed methods.

References

1. Tsubakimoto T, Kawamura M, Kumagai K, Matsubara H, Tanaka T, Hidaka K, Murashima T, Suzuki T, and Kobayashi K (2015), Camellia Dragons 2015 Team Description. Proceedings of the 19th Annual RoboCup International Symposium.
2. Tanaka T, Tsubakimoto T, Kawamura M, Kumagai K, Matsubara H, Hidaka K, Aizawa Y, Nakagawa M, Iwai Y, Suzuki T, and Kobayashi K (2016), Camellia Dragons 2016 Team Description. Proceedings of the 20th Annual RoboCup International Symposium.
3. Hidaka K, Tsubakimoto T, Tanaka T, Kumagai K, Matsubara H, Aizawa Y, Iwai Y, Nakagawa M, Futatsuishi K, Mori N, Ohkusu K, Takahashi K, Uemura Y, Ito K, Niwa H, Suzuki T, and Kobayashi K (2017), Camellia Dragons 2017 Team Description. Proceedings of the 21st Annual RoboCup International Symposium.
4. Aizawa Y, Hidaka K, Mori N, Ohkusu K, Takahashi K, Uemura Y, Chiba M, Hayashi K, Ito K, Nagami T, Shimizu Y, Ymada Y, Hosokawa K, Ito S, Kuboya T, Ohta G, Tachi T, Tanabe K, Tsubokura K, Suzuki T, and Kobayashi K (2018), Camellia Dragons 2018 Team Report. Proceedings of the 22nd Annual RoboCup International Symposium. Available online: https://github.com/CamelliaDragons/CamelliaDragonsCodeRelease.
5. Röfer T, Laue T, Müller J, Bartsch M, Batram MJ, Böckmann A, Böschen M, Kroker M, Maaß F, Münder T, Steinbeck M, Stolpmann A, Taddiken S, Tsogias A, and Wenk F (2013), B-Human Team Report and Code Release 2013. Only available online: http://www.b-human.de/downloads/publications/2013/CodeRelease2013.pdf.
6. Röfer T, Laue T, Müller J, Schüthe D, Böckmann A, Janett D, Koralewski S, Maaß F, Maier E, Siemer C, Tsogias A, Vosteen J (2014), B-Human Team Report and Code Release 2014. Only available online: https://www.b-human.de/downloads/publications/2014/CodeRelease2014.pdf.
7. Röfer T, Laue T, Richter-Klug J, Schünemann M, Stiensmeier, J, Stolpmann A, Stöwing A, Thielke F (2015), B-Human Team Report and Code Release 2015. Only available online: https://www.b-human.de/downloads/publications/2015/CodeRelease2015.pdf.
8. Röfer T, Laue T, Kuball J, Lübken A, Maaß F, Müller J, Post L, Richter-Klug J, Schulz P, Stolpmann A, Stöwing A, Thielke F (2016), B-Human Team Report and Code Release 2016. Only available online: https://www.b-human.de/downloads/publications/2016/coderelease2016.pdf.
9. Röfer T, Laue T, Bülter Y, Krause D, Kuball J, Mühlenbrock A, Poppinga B, Prinzler M, Post L, Roehrig E, Schröder R, Thielke F (2017), B-Human Team Report and Code Release 2017. Only available online: https://www.b-human.de/downloads/publications/2017/coderelease2017.pdf.
10. Kobayashi K, Kanehira R, Kuremoto T, and Obayashi M (2011), An Action Selection Method Based on Estimation of Other's Intention in Time-Varying Multi-Agent Environments. Lecture Notes in Computer Science, Vol.7064, pp.76–85, Springer-Verlag.
11. Kobayashi K, Kurano T, Kuremoto T, and Obayashi M (2012), Cooperative Behavior Acquisition in Multi-agent Reinforcement Learning System Using Attention Degree. Lecture Notes in Computer Science, Vol.7665, pp.537–544, Springer-Verlag.
12. Kuremoto T, Tsurusaki T, Kobayashi K, Mabu S, and Obayashi M (2013), An Improved Reinforcement Learning System Using Affective Factors. Robotics, Vol.2, No.3, pp.149-164.
13. Watada S, Obayashi M, Kuremoto T, Mabu S, and Kobayashi K (2014), A Decision Making System of Robots Introducing a Re-construction of Emotions Based on Their Own Experiences. Journal of Robotics, Networking and Artificial Life, Vol.1, No.1, pp.27–32.
14. Kawamura M and Kobayashi K (2014), An Action Selection Method Using Degree of Cooperation in a Multi-agent Reinforcement Learning System. Journal of Robotics, Networking and Artificial Life, Vol.1, No.3, pp.231-236.
15. Tsubakimoto T and Kobayashi K (2014), Cooperative Action Acquisition Based on Intention Estimation Method in a Multi-agent Reinforcement Learning System. Proceedings of the International Conference on Artificial Life and Robotics (ICAROB2014), pp.122–125.
16. Tsubakimoto T and Kobayashi K (2015), Cooperative Action Acquisition Based on Intention Estimation in a Multi-agent Reinforcement Learning System. IEEJ Transactions on Electronics, Information and Systems, Vol.135 No.1 pp.117–122 (in Japanese).
17. Alpaydin E (2009), Introduction to Machine Learning. The MIT Press.
18. Marsland S (2009), Machine Learning: An Algorithmic Perspective. Chapman and Hall/CRC.
19. Murphy KP (2012), Machine Learning: A Probabilistic Perspective. The MIT Press.
20. Bishop CM (2010), Pattern Recognition and Machine Learning. Springer.

Table 1. Official results at the RoboCup competitions

competition	main competition	drop-in player	technical challenge
RoboCup Japan Open 2014	1st (4 teams)	-	4th (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		
RoboCup Japan Open 2015	1st (4 teams)	-	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		
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	25 (26 teams)	-
	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		
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		
RoboCup 2017	1st Challenge Shield (12 teams)	-	Last 8 (PK Challenge)
	Final: Camellia Dragons 1 : 0 Berlin United		
	Semi Final: Camellia Dragons 3 : 0 JoiTech-SPL		
	Quarter Final: Camellia Dragons 2 : 0 MiPal		
	2nd Round Robin #1: Camellia Dragons 1 : 0 Robo Eireann		
	2nd Round Robin #2: Camellia Dragons 3 : 0 Astlan		
	Play-In Round: Camellia Dragons 0 : 1 RoboCanes		
	1st Round Robin #1: Camellia Dragons 4 : 0 Linkoping Humanoids		
	1st Round Robin #2: Camellia Dragons 2 : 0 Bembelbots		
RoboCup Japan Open 2018	1st (2 teams)	-	-
	Final: Camellia Dragons 4 : 2 IRUF		
RoboCup 2018	3rd Challenge Shield (12 teams)	-	Last 8 (PK Competition)
	Third Place: Camellia Dragons 4 : 0 UPennalizers		
	Semi Final: Camellia Dragons 3 : 0 NTURoboPAL		
	2nd Round Robin #1: Camellia Dragons 0 : 1 UPennalizers		
	2nd Round Robin #2: Camellia Dragons 3 : 0 Rinobot		
	2nd Round Robin #3: Camellia Dragons 3 : 0 MiPal		
	2nd Round Robin #4: Camellia Dragons 5 : 0 Aztlan		
	Play-In Round: Camellia Dragons 1 : 2 SPQR		
	1st Round Robin #1: Camellia Dragons 0 : 9 Nao-Team HTWK		
	1st Round Robin #2: Camellia Dragons 0 : 3 rUNSWift		