MRL-SPL
Team Description for RoboCup 2016

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Abstract. This article gives the team description and a concise explanation of research interests of MRL-SPL team, aiming to participate in RoboCup 2016 Standard Platform League. The presented document covers various subsections including perception, self-localization, and behavior control.

1 Introduction

MRL-SPL team, under the supervision of Qazvin Azad University (QIAU), is one of the research groups of the Mechatronics Research Laboratory (MRL), dedicated to work in the field of biped and mobile robots. MRL presence in RoboCup different leagues since 2002, results in numerous successful achievements both in the areas of research and competition. MRL-SPL team has been an active participant of world RoboCup since 2009. It's achievements are 2nd place in IranOpen 2013, 3rd place in German Open 2014, 1st place in IranOpen 2014, ranked among 5th top teams in RoboCup 2014, 2nd place in IranOpen 2015 and entrance in play-off games in RoboCup 2015. Detailed results are provided in Appendix 1. MRL is also willing to participate in RoboCup IranOpen 2016.
MRL is willing to compete in (1) outdoor team competition and (2) drop-in player competition. MRL is partially using B-Human code release 2013 (framework and motion modules) and obstacle detection module from their 2014 release and their work on whistle detection. Other parts (behavior, vision, self-localization, path planning and obstacle avoidance) of MRL code are developed by the team.

The team members of MRL-SPL are:
Undergraduate Members: Aref Moqadam Mehr, Mohammad Ali Sharpasand, Novin Shahroudi, Pooya Sagharichiha, Mohammadreza Hasanzadeh.
Graduate Members: Mohammad Ali Zakeri Harandi, Omid AmirGhiasvand, Meysam Farsi, Farzad Fathali Beyglou.
Team Leaders: Aref Moqadam Mehr, Mohammad Ali Sharpasand.

NAOs MRL-SPL Possesses: Two H21 V3.2, two H21 V3.3, one H21 V4, and four H25 V4.

2 Perception

2.1 White Goal Post Detection

The goal posts became white since RoboCup 2015, thus it is harder to detect the goal posts due to their similarity (in color) with background which is usually white too. So, instead of scanning the image and looking for some color-coded pixels, MRL has a new approach which is to find possible positions for goal posts by searching on the field boundary.
In this method, after the field boundary is extracted and its convex hull is calculated, any violation of white color to the field boundary will be marked as a potential goal post. These regions can be either goal post or robot. To distinguish these two kinds of objects there are

several sanity checks such as color gradient and relation between width, height and distance. Since these sanity checks could not reject all false positives, a Neural Network classifier has been utilized to learn the difference between a goal post and a non-goal post object (like robots' arms which can be extremely similar to a goal post). The potential goal post region is cropped from image and fed to this classifier which has learned the difference from a supervised training set.

2.2 Feature-based Image Processing

Since the objects in the SPL field are becoming less color-coded during the recent years, a less color-dependent approach needed to be utilized. MRL's former approach for image segmentation was based on vertical image scan-lines. In this approach, the scanner, breaks the image into vertical scan-lines based on a pre-configured color-table and then tries to merge results in order to achieve the color-based segmentation.
A new method, which is described in [3], is a segmenter module which clusters the image into different segments. This technique is not only much more efficient but also requires no pre-configuration.
After the segmentation, a feature matrix is calculated for each segment. This matrix has features such as color gradient and pixel diversity. It also includes some other more physical factors like mean distance to the horizon or mean distance to the field boundary. Field boundary itself is calculated by searching for convex hull in the green color. As described in [4], since most of the field is green, the green color can be defined as the most repetitive color in the image.
Afterward, each feature matrix (from each segment) is compared to the trained data set and then classified as an SPL object. To achieve this result the data set had to be created from a supervised learning method. The classification method MRL used is Neural Network, since it is fast and accurate.

3 Self Localization

The change in color of goal posts, has been strongly affected the reliability for localization as the most unique and well detectable landmarks in the SPL field. On the other hand, the previous localization method based on parallel Unscented Kalman Filters developed by B-Human[5] is highly sensitive to false detections and outliers. It has strong assumptions about zero-mean gaussian measurement error for objects like goal posts which leads to a solution heavily relying on accuracy of camera calibration.
MRL, however, has utilized a non-parametric solution for the self-localization problem to tolerate rare false detections and cope better with unknown-correspondence landmarks which are of an special importance for using lines for global self-localization. The commonly used and well-known method of Mixed Monte Carlo Localization[6][7] was selected. Field lines are considered in this method by extracting a point in every fixed interval of detected lines and matching them to a lookup table measurement model considering narrow gaussian error around each line. Goal posts and circles are also considered each with another lookup table measurement model.
This method has shown to have higher robustness in camera miscalibration since it mostly uses closer sources of information which are less disrupted by camera disposition.

4 Behavior Control

To get the benefits of identical team of robots, a dynamic role/post assignment based on the time cost of each robot toward a position in performing a task has been designed and implemented for RoboCup 2015 and is explained in MRL-SPL TDP 2015 [8].
As mentioned in previous sections lots of workarounds applied to overcome false positive detection of white goal posts, however in last year tournaments the localization module suffered much. Consequently, the post/role assignment algorithm in behavior layer had troubles as

it was basically depended on the distance of each robot to a target position, in other sense, localization of each robot. Although optimistic input for this method resulted in fine results specially in simulation tests, this incident proved that both a benchmarking method and a robust algorithm to erroneous input is required.

4.1 Strategy

During the last year competitions a couple of new behaviors have been added such as a supporter for goalkeeper. In these scenarios, goalkeeper may need cover until it kicks the ball off from the penalty area. Also a supporter for the teammate who owns the ball, wings to increase the chance of ball possession specially in one in one fights.
Fig. 1 & 2 depict result of role/post assignment with vectors v1 to v5 together with goalkeeper's dynamic border enabled [8] fending area. Other than GoalKeeper (labeled GK in figure 1) that always takes position in post GK, all other players take stationary posts labeled as DF, P1, P2, P3 in case of ball absence. In case ball is in the field and detected by the team, stationary posts will move as a function of ball position. More importantly a leader (LD) and maybe a supporter (SUP) role (based on strategy configurations of the game) will be assigned considering time costs calculated by the role/post assignment algorithm. Policy of playing with the ball (as leader/supporter) overwrites taking stationary positions, hence as long as a blue vector exists player will act upon that instead of the red one.

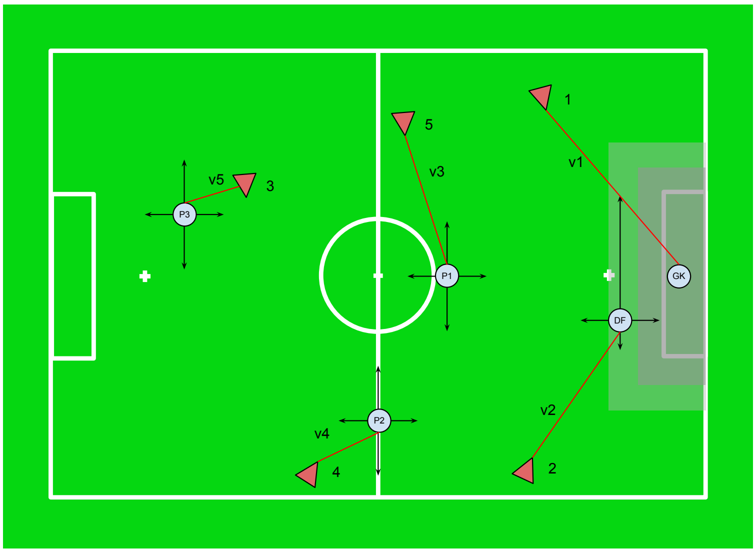

Fig. 1. Showing robots (red triangle), predefined positions as posts (blue circles), red vectors from robots to positions (result of post assignment), arrow vectors on positions (mobility range in x and y axes), goalkeeper fending area (gray rectangles), numbers next to each robot indicate their player number

4.2 Voting Mechanism

In behavior layer, calculations such as role/post assignment are performed distributed, therefore a synchronization mechanism is required to keep the team coordinated. A voting mechanism is implemented which helps to run voting on specific incidents. This mechanism is applicable in every scenario that a collective decision is required.

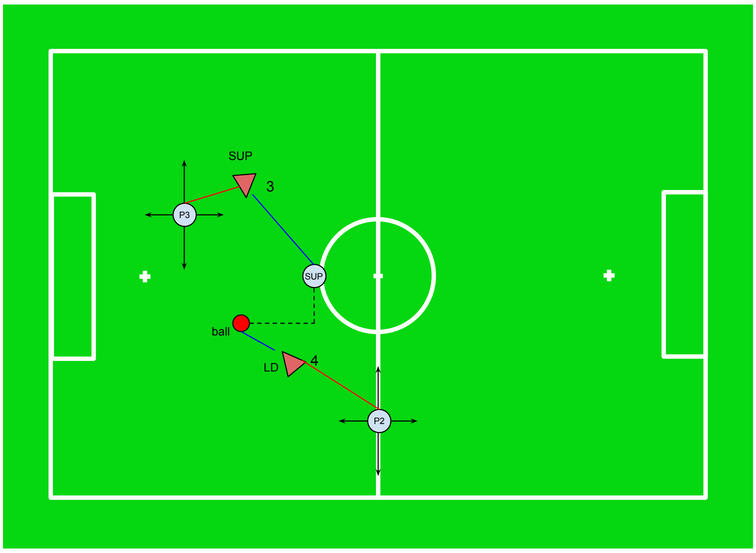

Fig. 2. Showing roles together with posts, red vectors from robots to positions (result of post assignment), blue vectors (result of role assignment), numbers next to each robot indicate their player number

5 Conclusion

For upcoming RoboCup a testing framework for benchmarking of behavior methods is going to be employed. Other solutions to task assignment problem is going to be studied and specifically the robustness of current method being targeted with some extensions. Behavior structure is going to be revised in order to meet drop-in game requirements.
Furthermore, MRL is working on a new walking engine and an automatic simultaneous camera and joint calibration (since they are extremely co-dependent).

MRL-SPL aims to produce a practical learning environment providing its university with detailed programs, including recruiting, training and an adaptation of agile paradigms for research-oriented projects. These conducted programs has impacted many other research centers of the university as well.

MRL-SPL has contributed in SPL with releasing its own code in 2013 including the behavior section. The team is currently working on a new architecture. Its main objective is to construct a framework to decouple and structure different modules so that cooperation can be done easier and faster. Generally, MRL is one of the advocates of the culture of open source, specifically Github community, and provides online repositories of the codes that can be useful.

6 Appendix 1

RoboCup Hefei 2015		
Round	**Opponent**	**Score**
Round Robin, Pool B	Linkoping Humanoids	8:0
	UT Austin Villa	2:1
	Austrian Kangaroos	4:0
	Nao Team HTWK	0:8
Play-in Round	NTU RoboPAL	1:2

RoboCup Iran Open 2015		
Match	**Opponent**	**Score**
1	Dutch Nao Team	3:1
2	Z-Knipsers	7:1
3	Berlin United	4:1
4/Final	Nao-Team HTWK	0:2

RoboCup Joo Pessoa 2014		
Round	**Opponent**	**Score**
Round Robin, Pool C	UT Austin Villa	3:1
	Nao Devils	0:2
	Cerberus	3:1
	NTU RoboPAL	2:1
Play-in Round	Austrian Kangaroos	3:0
Quarter Finals	rUNSWift	0:5

RoboCup Iran Open 2014		
Match	**Opponent**	**Score**
1	Dutch Nao Team	9:0
2	Dainamite	6:0
3	Berlin United	5:0
4/Final	Nao-Team HTWK	4:0

RoboCup German Open 2014		
Round	**Opponent**	**Score**
Round Robin, Pool A	B-Human	1:3
	Nao Devils	4:2
	Z-Knipsers	4:0
	Berlin-United	7:0
Semi Finals	**Nao-Team HTWK**	**1:4**
3rd Place	**RoboEireann**	**11:0**

References

[1] T. Rofer, T. Laue, J. Muller, A. Burchardt, et al, B-Human Team Report and Code Release 2010, http://www.b-human.de/downloads/bhuman10_coderelease.pdf

[2] T. Kastner, T. Rofer, T. Laue, Automatic Robot Calibration for the NAO, In RoboCup 2014: Robot Soccer World Cup XVIII. Lecture Notes in Artificial Intelligence, Springer (2015).

[3] P. F. Felzenszwalb, D. P. Huttenlocher, Efficient Graph-Based Image Segmentation, International Journal of Computer Vision Volume 59, Issue 2 , pp 167-181, 2004.

[4] T. Reinhardt, Master thesis, Kalibrierungsfreie Bildverarbeitungsalgorithmen zur echtzeitfahigen Objekterkennung im Roboterfussball, Leipzig, 2011.

[5] T. Rofer, T. Laue, J. Muller, A. Burchardt, et al, B-Human Team Report and Code Release 2013, http://www.b-human.de/downloads/publications/2013/CodeRelease2013.pdf

[6] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. Probabilistic Robotics. MIT Press, Cambridge, 2005.

[7] Thrun, Sebastian, et al. "Robust Monte Carlo localization for mobile robots." Artificial intelligence 128.1 (2001): 99-141.

[8] Omid Amirghiasvand, et al. "MRL-SPL TDP Description for RoboCup 2015." RoboCup 2014: Robot World Cup XIX. Lecture Notes in Artificial Intelligence, Springer (not yet published)

[9] Thomas Rofer, Tim Laue, Judith Muller, et al, B-Human Team Report and Code Release 2014, http://www.b-human.de/downloads/publications/2014/CodeRelease2014.pdf