MRL-SPL
Team Description for RoboCup 2017

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Abstract. This article provides a team description and a concise explanation of research interests and activities of MRL-SPL team, aiming to participate in RoboCup 2017 Standard Platform League (SPL). Approaching to the underlying real world problems, there are increasing scientific and pragmatic challenges in Perception, Self-Localization, Behavior, and Motion Control. To this end, a Fast Randomized Hough Transform (FRHT) algorithm is utilized to detect the ball with new features. Better positioning and passing are accomplished by detecting the unoccupied parts of the field. Adaptive mixed Monte Carlo Localization is used for estimating robot position in a dynamic and highly symmetric environment. Furthermore, integrating WiFi signals will contribute enhancing the accuracy of the localization. In terms of motion, robots perform more precisely as their joints and cameras are calibrated. This is achieved by a novel automatic calibration approach in which joints and cameras are simultaneously calibrated. Ultimately we are working on UNSW walk engine as well as following the longer path toward an open-source portable walking engine.

Keywords: RoboCup 2017, SPL, Standard Platform League, MRL

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 working in the field of biped robots. MRL presence in RoboCup different leagues since 2002 has yielded in numerous successful achievements both in research and competition. MRL-SPL has been an active participant of International RoboCup competitions since 2009. Its achievements are 2$^{\text{nd}}$ place in Iran Open 2013, 3$^{\text{rd}}$ place in German Open 2014, 1$^{\text{st}}$ place in Iran Open 2014, reaching quarter-final in RoboCup 2014, 2$^{\text{nd}}$ place in Iran Open 2015, entrance in play-in rounds in RoboCup 2015 & 2016 and 2$^{\text{nd}}$ place in Iran Open 2017.

Our team members consists of:
Undergraduate Members: Erfan Kouzehgaran, Sina Moqadam Mehr, Ali Sirouszia, Masoud Khairi Atani, Mostafa Hassan Poor, Sara Safar Abadi, Mohammad Ali Sharpasand, Aref Moqadam Mehr
Graduate Members: Mohammadreza Hassanzadeh, Farzad F. Bigelow
Team Leader: Novin Shahroudi

2 Code Usage

Since 2014 we have been using B-Human 2013 code release [1] with our own behavior-control, self-localization and vision modules beside the required modifications due to the rules change in each year. We upgraded to B-Human 2016 code release our modules ported to the latest infrastructure. We also planned portage of *UNSW RoboCup Team*'s motion modules with some modifications described in Motion Control section.

3 Impact

We have been an active participant of SPL league since 2009. We are one of the main teams participating in regional Iran Open RoboCup SPL competitions and promoting this league. We have had a couple of code releases and a team report[1] in 2013. Currently, some of our codes are available on our github and we are planning to release more of our codes and reports in the upcoming year.

We have been working hard to fill the gap between theoretical studies and practice in our university. As it is explicitly stated in our vision statement, we crafted a self-organized structure. During the last year, we have worked on a recruiting process that enabled many more people to join us and start self-driven research and development.

4 Perception

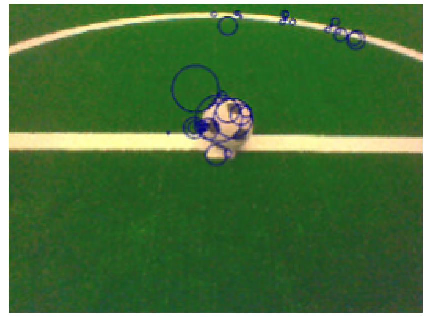
4.1 Black and White Ball Detection

Due to the ball color change in 2015, many attempts have been made for ball detection to be both effective and efficient. The current working method we use is Hough Transform circle detection on edged image which is described in following.

A stepwise edge detection with a resolution proportional to the pixel distance to the horizon is utilized. In this method, more pixels are involved near the horizon to enable detection of far objects which are smaller in the image and less in the bottom of the image in which objects are bigger. Then, Sobel filter is used for calculating edge points and a Fast Randomized Hough Transform (FRHT) [2] detects prospective ball segments. During FRHT, we refine edges that are

[1] MRL-SPL Code Release 2012, `http://mrl-spl.ir/en/research/publications`

(a) Edge and Hough Result



(b) FRHT Result

Fig. 1: (a) white points are stepwise detected edges and red lines are those that are refined during FRHT detection. (b) result of FRHT

used to add to their precision regardless of the selected resolution (Figure 1 - a). For the first step of validation, the size of the circle in the image, projected diameter of it, and white pixel percentage is checked. The resulting circles are passed to pentagon detection. In this part, a horizontal scan line runs on the edge image looking for black segments. After merging and validating the black segments, the number of them is used for the final validation of ball.

4.2 Field free part detection

Detection of free spaces of the field can be beneficial for the behavior control tasks, such as dribbling, passing, and positioning. In order to provide this data, the first step is to find the field color. For this purpose, the histogram of Cr channel of the image is calculated. The peak of this diagram is considered as the field color after being tracked and filtered in order to reduce noises and filter outliers.

Afterward, top points of the field are calculated using a vertical scan line. Then by utilizing Graham Scan method, the convex hull of the topmost green pixels is calculated. The resulting points are considered as field boundaries to determine whether a point lies in the field. In order to detect the free parts, a region growing segmentation is run on the area inside the convex hull to form green only polygons that represent free parts of the field. A center and a radius are then extracted and projected on the field to be used by behavior skills.

5 Self Localization

We have been working on Mixed Monte Carlo Localization (Mixed MCL) because it is capable of globally localizing the robot, friendly with multi-modal distributions and multi-hypotheses, and it enables us to better use ambiguous field features such as lines and goal posts. Besides, it can easily deal with occasional false positives. However, we are still working to enhance our MCL implementation.

Adapting number of particles can improve effectiveness and efficiency of our algorithm. It is proven that Adaptive MCL outperforms fixed number of particles. Our resampling strategy can also be improved so that the history would be better preserved. Currently, resampling occurs in every frame which may cause relying too much on incomplete measurements and sacrificing history. There is a significant difference in experimental results between simulation and real tests. Therefore, the measurement model we use requires some correction. On the other hand, odometry can be very advantageous to the overall performance of MCL and the current odometry data is not sufficiently accurate. Hence, we plan to utilize other data such as Inertia Measurement Unit (IMU) and combine the output to kinematic measurements in order to construct a better *a priori* knowledge. In addition, we are working on better solving the problem of the symmetrical field. We are going to use WiFi measurements as a complementary data. On the other hand, combining perceptions of teammates can pull the field out of symmetry. e.g.: dynamic objects like robots and the ball can be used to share models among teammates and reduce the chance of having a symmetric localization. There are also some features outside of the field to help such as game controller table, the histogram of colors, and sound signals.

6 Behavior Control

In previous years we implemented a basic formation system, passing mechanism and task assignment algorithm which enabled us to cover our high-level decisions in gameplay. Due to the essence of homogeneous teams of NAO robots, and to have an agile cooperative team of robots we used [3] as our task assignment algorithm. With some enhancements, our implementation minimizes the time that it takes for an agent to take a position. Currently, our general strategy is to dynamically assign robots to predefined formation position while one or more of them take position according to the ball, namely leader and supporter.

6.1 Strategies using Coach

We are adding a new factor which determines how much offensive or defensive our strategy must be. Coach is responsible for calculating this factor by observing the game field. Its interpretation of opponent strategy and formation, the average time the ball was in our field, the number of robots, time left, and goal differences can all be strategically important. Knowing how defensive or offensive robots should play can specify how many defenders we need, how robots can score a goal, and so forth. Our formation positions are a function of game states, the number of field players, and the ball position. This function can be improved by taking into account the free spaces of the field. A coach can also be considered for another vote to better synchronize the team. A voting mechanism can be ineffective when few robots are playing. A coach can act as an extra agent(vote).

The only difference is that its vote is generated based on other players' opinion. This solution reduces the chance of wrong decisions, hence keeping the team synchronized.

6.2 Other Works

Toward possible improvements, the passing mechanism can be integrated into task assignment algorithm. Currently, this mechanism works in one way. An agent finds appropriate spaces to pass to. However, it can work both ways. The second agent (pass-taker) gets in position prior to the execution of the pass action by the first agent. We are also eager to evaluate the feasibility of using SCRAM [4] in SPL. Furthermore, we are planning to add more behavior skills to be more competitive.

7 Motion Control

Stable walking and accurately locating objects detected by vision are vital for an SPL game. Most common methods for both of them heavily rely on knowing accurate joint angles and camera pose and are sensitive to the errors in joint sensors and camera displacement. However, it is not viable to calibrate these parameters separately.

7.1 Auto Calibration

After a careful observability analysis, we have designed an automatic simultaneous joint and camera calibration. In our approach the robot stands on a calibration plate with accurately known dimensions, having its feet fixed in a template. It then observes a marker from several positions and collects measurements. Finally, calibration parameters for 13 joints of legs and neck as well as extrinsic parameters of both cameras are extracted using a batch optimization based on the method of Levenberg-Marquardt.

7.2 Improve UNSW Australia walk and kick stability

The walking engine released by UNSW has proved to be stable and reliable. However, there are still some drawbacks. First, it happens during collisions that robots fall down and it is necessary to avoid it. Since it is not always possible to reject a sudden disturbance, we need to recover from pushes. We have planned to implement a push recovery strategy based on step planning. Second, there is no control to keep Center of Pressure (CoP) in foot convex hull which can save robots from falling. To this end, a torque transformer which enables a position-controlled robot to be controlled by torque command is proposed. It helps us to control CoP using ankle joints. Third, it is quite feasible in UNSW approach to keep knees straight which can prevent robots from heating up. We have been working on Singularity-Robust Inverse Kinematics (SR-IK) and that is what it takes to keep the knees straight.

7.3 Portable Biped Walk Library

A promising direction for future research in motion would be to build a portable biped walk library: a new open source walking engine with ZMP preview control. Also, it will be portable for usage in other frameworks and languages like MATLAB and as SPL culture demands, we prefer to keep it standardized and hardware independent to be even portable for usage on other biped robots.

8 Conclusion

MRL-SPL has been an active RoboCup participant, having important impacts on its own community and working hard to overcome the new challenges of the SPL. From the aspect of vision, FRHT is used to detect the new ball. Free parts of the field are detected to enhance positioning and passing. On the other hand, Adaptive mixed Monte Carlo Localization is used for the purpose of estimating robot position. As an ongoing research, to have the robot precisely localized, an RF-localization based on WiFi signals is considered. A coach robot determines how offensive/defensive the robots should play. More precise perception and motion will be achieved through auto-calibrating robot joints and cameras. There are as well, a number of ongoing contributions on UNSW walk engine. At last, an open-source and portable walking engine is being developed based on the concept of ZMP preview control strategy.

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