NTU RoboPAL
Team Description for RoboCup 2012

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Abstract. This team description paper describes the organization, research focus and ongoing work of the NTU RoboPAL team entering the RoboCup Standard Platform league in 2012.

1 Introduction

Team NTU RoboPAL has been participated in the RoboCup Standard Platform League (SPL) competitions since 2009. We were in the top 8 teams in 2009, in the top 16 teams in 2010, and won the 3rd place in 2011. The current team members consists of the following persons:

– *Chieh-Chih Wang* is an associate professor in computer science and information engineering and the director of the Robot Perception and Learning Laboratory. His research is in the areas of robot perception, computer vision and machine learning.
– *Chun-Hua Chang* is a PhD student in computer science and information engineering. His research involves SLAM in dynamic environments and tracking. He has been a team member since August 2009.
– *Chih-Chung Chou* is a PhD student in computer science and information engineering. His research involves motion control, obstacle avoidance, planning and POMDP. He has been a team member since August 2011.
– *Kai-Chieh Ma* is an undergraduate student in computer science and information engineering. His research involves robot perception. He has been a team member since August 2011.
– *Chun-Kai Chang* is an undergraduate student in computer science and information engineering. His research involves robot perception. He has been a team member since August 2011.
– *Bang-Cheng Wang* is an undergraduate student in computer science and information engineering. His research involves locomotion, control, obstacle avoidance and planning. He has been a team member since August 2011.

The following sections describe our research focus and ongoing work.

2 Research Focus

Our scientific interests are driven by the desire to build intelligent robots and computers, which are capable of servicing people more efficiently than equivalent manned systems in a wide variety of dynamic and unstructured environments. We believe that perception and learning are two of the most critical capabilities to achieve our goals. The RobotCup Standard Platform League provides an excellent scenario for us to exploit and explore robot perception and learning.

2.1 Simultaneous Localization, Mapping and Moving Object Tracking

Simultaneous localization, mapping and moving object tracking (SLAMMOT) involves both simultaneous localization and mapping (SLAM) in dynamic environments, and detecting and tracking these dynamic objects. Our SLAMMOT work [1, 2] provides a foundation for robots to localize themselves and to detect and track other teammates and opponents in the RoboCup scenario with a given map. In addition to LADAR-based solutions, we have proposed solutions to stereo-based SLAMMOT [3] and monocular SLAMMOT [4].

2.2 Simultaneous Localization and Tracking

Localization and moving object tracking are key components for robots to exhibit intelligent behaviors. Based on the theoretical foundation of SLAMMOT, our Simultaneous localization and tracking (SLAT) algorithm integrates information from multiple teammate robots and provides the estimates of the teammate robot poses and the opponent robot positions simultaneously [5]. With the more robust and accurate state estimates, it would be more feasible to design and perform better strategies to play soccer games. Our experiments also show that the localization performance can be boosted by integrating moving object tracking, which is especially useful for the cases where self-localization is challenging. For example, when a robot is focusing on a ball, it is still possible to accomplish localization through the teammates' knowledge on the ball position even map features are insufficient for self-localization.

2.3 Localization in Highly Dynamic Environments

State-of-the-art localization approaches often rely on the static world assumption using the occupancy grids. However, the real environment is typically dynamic. In [6], we propose the feasibility grids to facilitate the representation of both the static scene and the moving objects. The dual sensor models are introduced to discriminate between stationary and moving objects in mobile robot localization. Instead of estimating the occupancy states, the feasibility grids maintain the stochastic estimates of the feasibility states of the environment. Given that an observation can be decomposed into stationary objects and moving objects, incorporating the feasibility grids in localization yields performance improvements over the occupancy grids, particularly in highly dynamic environments. Our approach is extensively evaluated using real data acquired with a planar laser range finder. The experimental results show that the feasibility grid is capable of rapid convergence and robust performance in mobile robot localization by taking into account moving object information. A root mean squares accuracy of within 50cm is achieved, without the aid of GPS, which is sufficient for autonomous navigation in crowded urban scenes. The empirical results suggest that the performance of localization can be improved when handling the changing environment explicitly.

2.4 Locomotion, Obstacle Avoidance and Navigation

We have demonstrated the wide angle kick module in 2010 which allows our robots to efficiently adjusting ball kicking directions. However, it was not fast and stable enough to be practicable in intense games. In 2011, we have built better wide angle kicking as well as designed side kick motion patterns so that the robots can perform ball kicking as soon as possible. For the goalie, we have designed an agile diving motion to rapidly react to potential attacks.

The sonar sensors are currently utilized by many teams to avoid colliding with other robots. However, the sonar sensors can only detect obstacles farther than 30cm. The measurements closer than 30cm, nevertheless, are still critical in the situations such as a number of robots are chasing the ball closely. In addition to sonar measurements, visual images from the onboard cameras are used and fused under our SLAT framework for accomplishing robust obstacle avoidance.

Navigation plays a key role in RoboCup. The nearness diagram (ND) navigation method and the dynamic window approach (DWA) are two of the most popular navigation approaches in the literature. We have proposed a self-tuning ND navigation approach [7] to obtain smoother robot trajectories and a DWA* approach [8] to determine the optimal control policies.

2.5 From RoboCup to Driving Safety

Cars able to drive autonomously have been demonstrated over the last years in the 2005 DARPA Grand Challenge, the 2007 DARPA Urban Challenge [9] and by the Google Driverless Car project [10]. These projects have attracted significant attention globally. High-end sensors such as 3D laser scanners are critical to accomplish the challenging perception problems in both urban areas and at highways. However, these single-robot perception approaches still have limited visibility due occlusion by nearby moving entities and the limited range of their sensors. In [11], it is shown that cooperative perception can achieve sufficient accuracy by combining lower-cost sensors such as 2D laser scanners and stereo cameras with vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication provided by dedicated short-range communications (DSRC) technology.

Single-robot perception approaches only insure their own driving safety and still have limited visibility, while in the cooperative perception all moving entities contribute by sharing their scene understanding. The localization and tracking accuracy is increased and there will be less visibility issues in the proposed framework. Our simulations show that the suggested multi-vehicle SLAT could achieve localization with sub-meter accuracy using stereo cameras only. With the use of 2D laser scanners, the reliability and robustness of the whole system can be assured as well as an increase of accuracy.

3 Ongoing Work

Our RoboCup SPL 2011 team report and code release are available in [12] in which our contributions are described in detail. Whilst our software system in 2011 was built based on the 2010 code release of the B-Human team[13], our system for RoboCup 2012 is being developed based only on the Aldebaran API and the walking engine by Aldebaran is applied directly. All the main perception and action modules are designed and developed by the NTU RoboPAL team members. Based on our previous academic contributions and RoboCup SPL accomplishments, we are currently working on the following tasks.

3.1 Software Architecture

The overview of our system is shown in Fig. 1. Regarding the perception module, the odometry and the image are retrieved from the Nao platform through the Aldebaran API, and then a set of detectors are executed to extract map and moving object features from the image. The odometry data and the map and moving object features are shared among all the teammates, so that all the teammates can see what the others see and know how they move. Based on the set of the odometry data and the map and moving object observations from all the teammates, our Cooperative Localization and Tracking (CLAT) algorithm enhanced with Multiple Hypothesis Tracking (MHT) estimates the states of all the teammates, the opponents, and the ball, which server as the input to our behavior engine. According to the states of the robots and the ball, our behavior engine first computes the team formation, which encodes the target poses for all the teammates, and each teammate robot will be assigned to a role according to their current state. For each role, the state machine is designed for the detailed behaviors. The behavior engine then sends commands to the walking engine and the special action engine.

3.2 Perception

In this perception module, two functions are significantly improved.

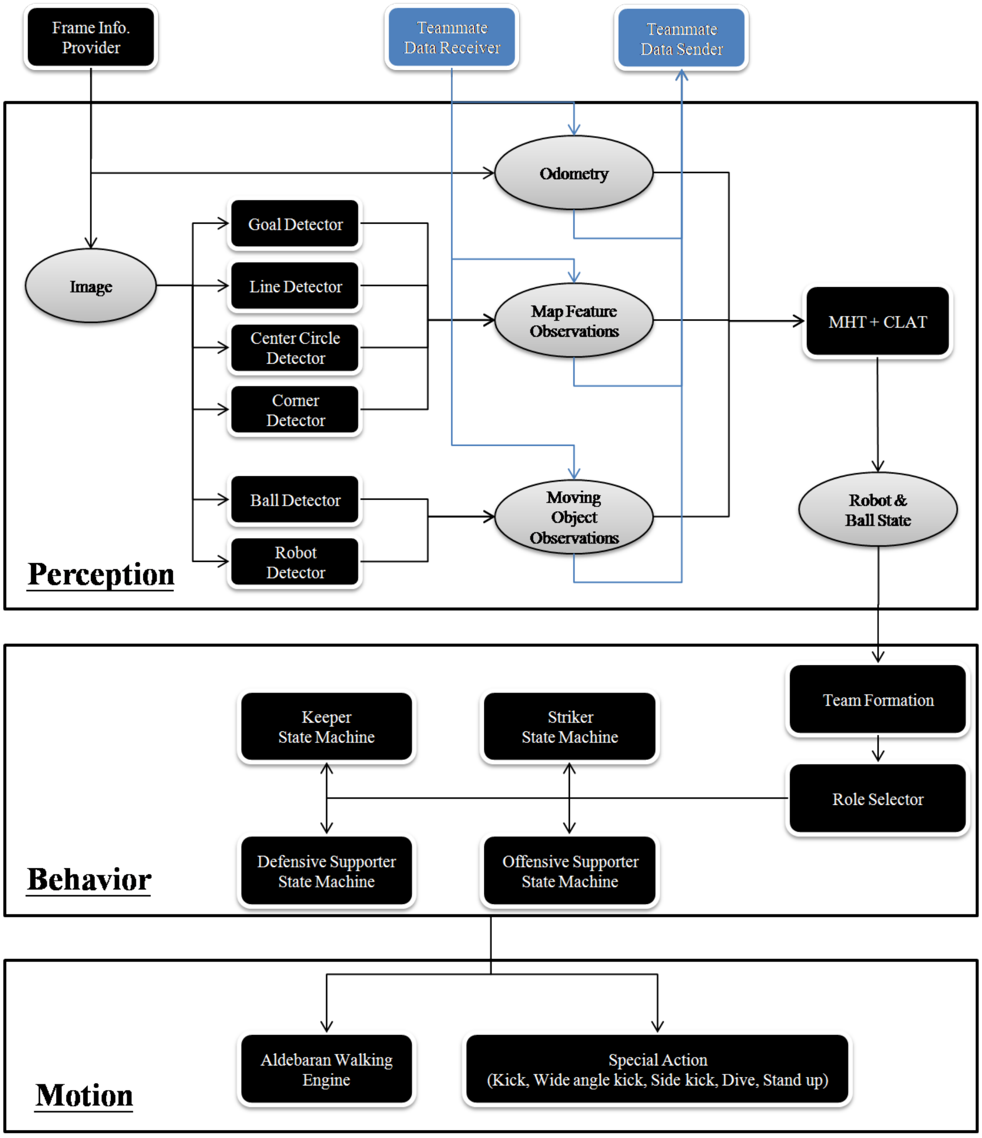

Fig. 1. Software Architecture

Field Line and Robot Detection detecting field lines and robots is critical for perception such as robot localization and tracking and for action such as high-level behavior control. However, classification of the filed lines and robots are challenging as both of the field lines and robots are white colored in SPL. Based on the observation that the edges of field lines (strong edges) are almost straight while the edges of the robots (weak edges) are curvy, we propose to classify strong and weak edges by multi-level thresholding. Using the lower thresholds, both weak edges and strong edges can be detected, but only strong edges can be detected using the higher thresholds. The proposed field line and robot detection algorithm is being verified and is demonstrated to be reliable.

Multiple Hypothesis Tracking (MHT) Enhanced Cooperative Localization and Tracking (CLAT) Our cooperative localization and tracking (CLAT) algorithm achieves accurate pose estimation for all the robots and the ball by incorporating data from all the teammates. However, one of the most critical challenges is the data association problem in which the object detected in the image, e.g. the goal, the robot, etc., has to be associated with one in the current belief. This problem is especially important for the SPL scenarios because in this year both of the goals are in the same color, yellow, and all the robots on the field look quite similar. Note that the belts with different colors are often occluded and can not be used to reliably differentiate robots. To deal with the data association issue, we enhanced our CLAT with the MHT algorithm: when a new observation comes, if multiple possible associations exist and currently theres no apparently best one, instead of making the hard decision, the algorithm adopts all of them. By maintaining and tracking all the possible hypotheses, the algorithm makes the decision after the result gets obvious which significantly improves the robustness of our perception system.

3.3 Action

In the action module, the improvement of the move-to-goal behavior and the design of team formations are described.

Move-to-Goal Behavior Our move-to-goal behavior in 2011 consists of a move-forward motion and two individual pure rotating motions. Though this behavior can drive the robot to reach the goal, it is rather redundant. Especially for kicking the ball, the robot is expected to follow a fast and smooth trajectory to reach the proper kicking pose without spending extra time to rotate and turn around the ball. We are implementing a planning module based on our work [8].

Team Formations Team formation defines the behavior of the whole team but not an individual robot. For instance, in an offensive formation, all robots except keeper should become strikers and move toward the opponent's goal. In a defensive formation, all robots should move around their own goal to help the keeper block the ball. In each situation, a proper formation should be chosen according to the current ball position, robot poses and the score. The concept of team formation helps to simplify the problem of multi-robot planning and cooperating behavior design. New team formations for different situations are being designed and verified this year.

Acknowledgements

We gratefully acknowledge the financial and administrative support from the Intel-NTU Connected Context Computing Center and Department of Computer Science and Information Engineering at National Taiwan University. This work was supported in part by National Science Council, National Taiwan University and Intel Corporation under Grants NSC 100-2221-E-002-238-MY2, NSC 100-2911-I-002-001, and 101R7501

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