Aztlan
RoboCup SPL 2016 Team Description

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Abstract

The Aztlan team integrates the previous teams Cauhpipiltin and UTH-CAR from five different mexican institutions: UNACAR, ITAM, CIMAT, DEMAT-UG, and IPN.

I. Team Information

The Aztlan SPL team is being formed to participate in RoboCup 2016 as a collaborative effort of the following Mexican institutions: ITAM, CIMAT, DEMAT-UG, UNACAR, IPN, and UTH. This team combines different levels of experience at RoboCup. Our team members are (in alphabetical order):

Students: Luis Daniel Bravo Ramírez (CIMAT, DEMAT-UG) Irving Francisco Camas Sarao (UNACAR) Daniela Monserrat Ceballos Zavala (CIMAT, DEMAT-UG) Gildardo González Rebolledo (ITAM) Marco Isaac Marin Granados (ITAM), Eduardo Alexis Romo Almazán (CIMAT, DEMAT-UG) Daniel Silva Medina (UNACAR) Francisco Mendoza Ruiz (UNACAR) Francisco Valente Castro (CIMAT, DEMAT-UG) Raúl Vargas Arriola (CIMAT) Franco Humberto Villella Romero (ITAM), Oscar Alberto Zavala Salas (UNACAR)

Team Leaders: Héctor Becerra (CIMAT), Claudia Esteves (DEMAT-UG), Jean-Bernard Hayet (CIMAT), Marco Morales (ITAM), Alberto Petrilli (UNACAR), Diego M Reyes (UTH), Humberto Sossa (IPN)

Our website and videos can be found at:

Web Site – http://robotica.itam.mx/spl

Classification video –http://robotica.itam.mx/videos/aztlan-qualification-robocup-spl-2016.mp4

II. Robot Information

Our combined team currently has the following robots:

- ITAM: 4 H21 V3.2 (intend to update all of them)
- CIMAT-DEMAT-UG: 2 H25 V4
- CIC-IPN: 5 H25 V4

III. Preference

Our preference to participate is in the following order: (1) Indoor team competition, (2) Drop-in player competition, (3) Technical challenges.

IV. Code Usage

No code from other teams is used. We develop our own code and we keep using code developed by our members for the Eagle Knights team, for the Cuauhpipiltin team and for the UTH-Unacar team.

V. PAST HISTORY

The participation of our members in the RoboCup Standard Platform league date back to 2005. The ITAM team was founded as Eagle Knights in 2003 and participated in the RoboCup SPL in 2005, 2006, 2007, 2008, and 2009. Later on, the ITAM team joined with CIMAT, DEMAT-UG, and UNAM, to participate as Cuauhpipiltin in RoboCup 2012. Later on, UNACAR, UTH, and IPN participated as the UTH-CAR team in RoboCup 2014 in the drop-in competition. This year we are joining efforts in order to build a stronger team able to cope with the challenges of the RoboCup.

Locally, in México, there have been efforts to promote a Standard Platform League competition in the Mexican Robotics Tournament/RoboCup Mexican Open since 2011. We had exhibitions in 2011, 2012, 2013 and 2014. In 2015 we had the first official competition where the Eagle Knights team from ITAM achieved 1st place and the Balam team from UNACAR achieved 2nd place.

VI. IMPACT

We believe that the collaborative efforts to create the Aztlan team will have a positive impact on the Standard Platform League and on our institutions. The collaboration will allow us to better prepare our a better team in the coming years that will promote the SPL league in México. It will also allow us to motivate our students to pursue the challenging problems in the league. Also, we will be able to address more challenging problems due to the complementary skills of the teams in each institution. Our students will be better trained. This will also enable us to be more competitive giving more prestige to our institutions.

VII. CURRENT ABILITIES AND PLANNED DEVELOPMENTS

Our main research interests include vision, localization and motion planning and control. At the integration of the team our main challenge is the development of a modular system that can be developed collaboratively.

The current architecture of our system is modular. The **Object Detection** module is in charge of taking visual information from the robot cameras and giving as output the detected object properties (e.g., position, orientation and size). Currently the detected objects are the ball, the goals, white-lines and in the near future other robots. Object properties are the input to the **Localization** module, which outputs an estimated absolute 2D position of the robot inside the field. The detected objects together with the estimated position and the **robot internal state** are compiled by the **World Representation** module and stored in the shared memory. The **Decision** module uses the **World Representation** and the **information from the Game Controller** in order to determine the best **Actions to be executed**.

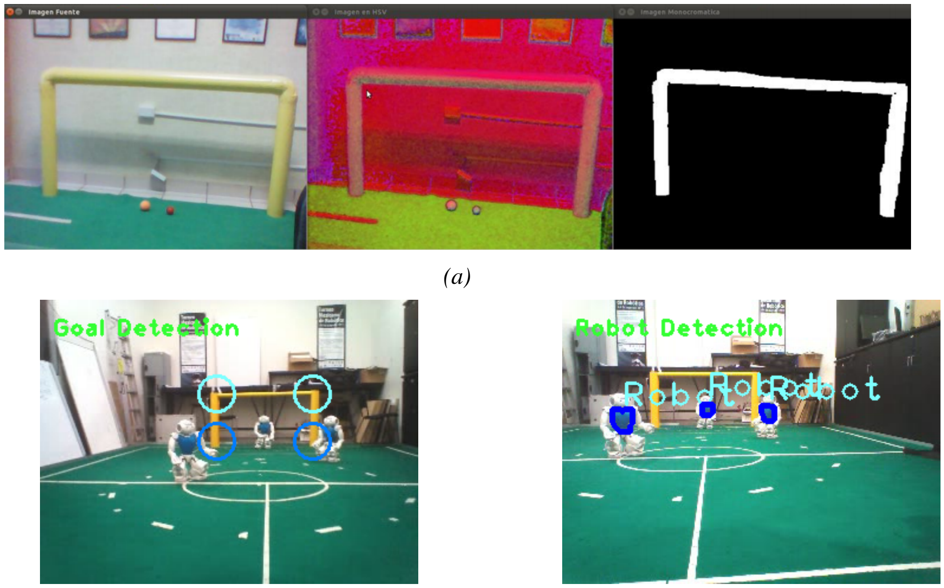
Below we provide more details on different problems addressed by our system.

A. *Object Visual Detection*

We are merging two previous modules. One module, developed by Master students at CIMAT, identifies the ball, the goal, and the white lines. The other module, developed at UNACAR, detects robots and the goal.

The CIMAT module efficiently segments objects in the HSV space at QVGA resolution from any of the two cameras (which of the two being determined by the Decision module). As other teams do, we rely on scan-lines-based image processing algorithms for the color segmentation and we perform the object detection among the line segments found along these scan-lines, which alleviates the computational burden. We also heavily incorporate geometric knowledge that we gather from the robot joints: With the horizon line, we can restrict the segmentation to the lower part of the image, i.e. for objects on the field; With the image-to-field homography (that maps coordinates in the image to coordinates in the robot frame), we can filter out spurious object detections, e.g. detected balls with image radius not consistent with the homography and the real ball radius; With the joints information, we roughly define an image mask of the robot self image (which is particularly important when using the bottom camera). We are currently quite satisfied of the goal and ball detection system, and are improving the white line detection in order to be able to offer a wider range of observations to the localization module.

The UNACAR module gets video in YUV model and efficiently applies color segmentation directly using Open CV. It binarizes the orange, white, green and yellow as shown in Fig. 1a. We already detect goals as shown in Figure 1b and robots as shown in Fig. 1c.



(a)

(b) *(c)*

Fig. 1: (1)Binarization of colors. (2) Goal Detection. (3) Robot Detection

B. *Localization*

One challenge we have with our new collaboration is to integrate the previous modules developed separately at CIMAT and at UNACAR.

UNACAR localization We have a localization module developed at UNACAR based on the Monte Carlo method and Kalman filters. We use a conformal model, where the two views are fused in an extended 3D horopter model. For visual simultaneous localization and mapping (SLAM), an extended Kalman filter (EKF) technique is used for 3D reconstruction and determination of the robot head pose. In addition, the Viola and Jones machine-learning technique is applied to improve the robot relocalization. The 3D horopter, the EKF-based SLAM, and the Viola and Jones machine-learning technique are key elements for building a strong real-time perception system for robot humanoids.

CIMAT localization. We have a functional absolute localization module developed at CIMAT based on a classical particle filtering strategy, i.e. that maintains a probabilistic, sample-based representation of the robot position and orientation. For the moment, it integrates only goal posts as observations, and works well with them. A very short-term goal is to add white lines as a second cue, in the form of quadrangles. In both cases, different strategies are being evaluated (1) to form the observation vector from image cues: point positions, distances along the horizon lines, angles to vanishing points. . . and (2) to propose well adapted noise probabilistic models for these observations.

Active localization. As the theme of one of the team members Master thesis, we are currently evaluating motion strategies based on stochastic optimal control, for implementing the idea of active localization in a context of particle filtering, based on similar works in target tracking [1]. The idea would be not only to control the robot head for improving the localization, as other teams do, but also to give speed controls for moving on the field.

C. *Decisions*

Our robots make decisions based on a finite-state machine. Transitions between states are determined based in the position of the ball, and position of the ball. Thus, we rely heavily in the quality of the object detection and localization. We currently have the following states: (1) Track Ball (TB), (2) Localization of Ball Position (LBP), (3) Robot Turn (RT), (4) Robot Positioning at the Ball for Kicking (RPBK), (5) Robot Slide(RS), and (6) Kicking the Ball towards the Goal(KBG).

D. Motion Planning and Control

Motion Planning is the main research field of some of the authors of this proposal and as such they have contributed with planners for humanoid robots and with adaptive sampling-based planning [2], [3], [4], [5]. In this regard, the first priority for a motion planning strategy for the team is to implement a local motion planner, the Nearness Diagram (ND) [6] to avoid other robots in the field and navigate through them toward the ball or the goal. Our plan is to also to develop a multi-layered motion planning and control as follows:

Role selection. We define a set of roles that the players can achieve during the game, each role is assigned a function to dynamically compute a set of candidate goals for state and environment variables relevant to achieve it. For example, one of the roles could be to intercept the ball, the function uses the estimation of the position of the ball and self-localization to determine a desired position for the robot. In addition, following ideas in [7] we can arbitrate among the available roles.

Sequence planner. In order to achieve the state and environment variables for the selected role, a sequence of actions to achieve them is planned. General states observed in the games are associated a small set of typical actions. Our initial approach is to use an A* [8] planner to simulate a few steps ahead in order to choose an appropriate sequence of decisions. In our current agenda we will explore techniques similar to those in [9] that apply demonstration-guided learning and sampling-based motion planning to train controllers that are robust to the presence of obstacles.

Composition of controllers. There is a set of available controllers that implement the most basic skills of the robot. This collection of motion primitives is vast enough to allow the robot to perform all the roles it can be assigned in the game. We follow the ideas in [7] to arbitrate among the available controllers.

Individual controllers. We are developing all the controllers to cover the needs of the robot, we provide more details below.

Locomotion. We currently use the locomotion controller from Aldebaran Robotics [10].

Kinematics. A generalized inverse kinematics algorithm [11], [12] has been implemented to generate whole-body motions for the Nao. This implementation was done to have additional and lower level control than the whole-body control provided by Aldebaran. The implemented algorithm gives a numerical solution to various input tasks, each of them with a different order of priority. Such a prioritized strategy works by projecting the tasks with less priority on the null-space of the Jacobian matrix of the tasks with higher priority. Currently supported tasks are: (1) to reach a position/orientation in 3D space with an end-effector (hands or foot) (2) to direct the gaze of the robot to a desired location in 3D space and (3) to keep the center of mass (CoM) inside the support polygon of the robot.

Adaptive kicking. A strategy very similar to [13] is being implemented to produce a kicking motion that adapts to the current ball position and the direction to the goal. The position of the ball is extracted from the recognition module and the localization module provides the orientation or the robot relative to the goal. Before kicking, the robot makes sure that the ball lies within the reachable space of its feet. If the ball is not inside the reachable space, the robot has first to approach to it. Depending on the position of the ball and goal relative to the robot, the left or right foot is chosen to perform the kick using the kinematics controller.

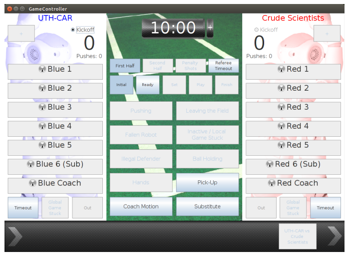
Adaptive goalie. As in adaptive kicking, a goalie is implemented to adapt to the ball position/direction.

E. Team Coordination

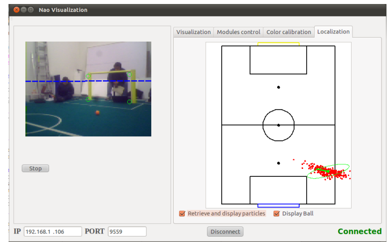
We are working on the development of algorithms of cooperation between agents. We are using a centralized control where the goalkeeper gathers information computed by all other modules in a 2D stochastic map. The goal is to maintain at least the position of its teammates in the field, the position of the other team robots and the position of the ball, by fusing the related metric information coming from all the robots and from its own sensors. Every time a teammate needs information to decide its next action, it will ask the goalkeeper. Also, messages will be sent to the appropriate players to query for information that is either unavailable m or which has low reliability.

F. Utilities

We are already using the GameController as shown in Fig. 2a. Also, a **visualization interface** (Fig.2b.) has been developed in Qt and C++. It allows us to connect to a robot and have a synthetic view on the current robot state, to evaluate the performance of the visual detection and localization modules, to interact with them for tuning and calibrating parameters.



(a)



(b)

Fig. 2: (a) Communication with Game Controller. (b) Visualization and module control interface. On the left side the image seen by the robot camera is displayed. The average goal observation among particles is shown in green and the horizon line in blue. On the right side the particle distribution of the Localization module is shown in red and the estimation position and orientation of the robot is depicted in green.

VIII. Conclusion

In this document we presented the Aztlan Standard Platform team. We want to stress that our team results from the collaboration between several education and research institutions of Mexico, (2) that our joint project has as a long-term goal to build a competitive team, and (3) that it has already generated and will generate in the next months a lot of enthusiasm among students and researchers, translating into challenging RoboCup-related projects in courses such as Advanced Programming, Probabilistic Robotics, Computer Vision, Computer Graphics, and Research Seminar.

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