UChile Robotics Team
Team Description for RoboCup 2016

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Abstract. This Team Description Paper describes the organization, publications, and new developments of the UChile Robotics Team for the RoboCup Standard Platform League 2016 in Leipzig, Germany.

Keywords: RoboCup, SPL, Standard Platform League, 2016, Universidad de Chile

1 Introduction

UChile Robotics Team (UChileRT) is a joint effort of the Advanced Mining Technology Center (AMTC) and the Department of Electrical Engineering of the Universidad de Chile in order to foster research in mobile robotics, computer vision and learning algorithms.

Our team was created in 2002 under the name UChile1, and we participated in the four-legged Standard Platform League since 2003. In 2007 we changed our name to UChile Kiltros, and in 2010 we collaborate with the SPQR Italian team. After the unsatisfactory results obtained in 2012 we carried out a restructuring process, where several changes and improvements have been implemented until now. As a result, we were within the top twelve teams in RoboCup 2013 (The Netherlands), and we reached the fourth place in both RoboCup 2014 (Brazil) and RoboCup 2015 (China). For the RoboCup 2016 we have developed several changes according to the rule changes and the technical challenges. In addition, several improvements have been developed in both robot algorithms and strategy in order to maintain the results obtained the last years.

This paper is organized as follows: First, we introduce the main publications presented and accepted for the RoboCup Symposium 2016 related with the team activities (Sec. 3), followed by the developments and changes for 2016 (Sec. 4). Finally, in Sec. 5, we also acquaint the current research lines guided by the doctoral and master thesis projects of some members.

2 Past Relevant Work and Scientific Publications

UChileRT has been involved in RoboCup competitions since 2003 in different leagues: Four-legged 2003-2007, @Home in 2007-2012, Humanoid in 2007-2009, and Standard Platform League (SPL) in 2008-2012. UChile's team members have served RoboCup organization in many ways: Javier Ruiz-del-Solar was the organizing chair of the Four-Legged competition in 2007, TC member of the Four-Legged league in 2007, TC member of the @Home league in 2009, Exec Member of the @Home league between 2009 and 2015, and co-chair for the RoboCup 2010 Symposium.

Among the main scientific achievements of the group are the obtaining of four important RoboCup awards: RoboCup 2004 Engineering Challenge Award, RoboCup 2007 and 2008 @Home Innovation Award, and RoboCup 2015 Best Paper Award. UChile's team members have published a total of 37 papers in RoboCup Symposium (see Table 1), 27 of them directly related with robotic soccer, in addition to many papers in international journals and conferences.

Table 1. Presented papers in the Robocup Symposium by year

RoboCup Articles	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Oral	1	2	1	1	2	3	2	2	-	-	1	1	1	-
Poster	1	1	1	-	3	2	-	-	2	1	2	1	4	2

3 Publications in RoboCup Symposium 2016

3.1 Robot Tracking[5]

In this paper we present a new method for tracking robots, using Random Finite Sets (RFS). Standard approaches use Kalman filters to keep position estimations of the robots, where several heuristics are aplied in order to eliminate and merge hypotheses. In this context a different approach is proposed, using the Probability Hypothesis Density: Mixture of Gaussians implementation (GM-PHD) of the RFS framework, which allows to overcome most of the current drawbacks in standard methods. The presented implementation uses finite sets instead of vectors, represented by a mixture of Gaussians, for both observations and obstacles, which encapsulates positions and quantity uncertainty by associating a weight value to each Gaussian. Obstacles are not associated each with a Gaussian, instead each Gaussian stores an estimation of the number of robots it represents.

This implementation shows a better performance than the EFK standard approach, dealing with most of the data association problems, being fairly successful.

3.2 Decentralized Reinforcement Learning[12]

Reinforcement learning (RL) has been increasingly used to learn complex behaviours for robots in the real world. One of the main challenges is the large number of training trials required, especially in systems with many state and action variables. For such problems with multi-dimensional action spaces, distributed reinforcement learning is often used to address this issue. In this context, we propose a Decentralized Reinforcement Learning (DRL) approach, which decomposes a problem in several learning tasks, or sub-problems, whose information and resources are managed separately and these tasks work together toward a common goal.

This work presents a decentralized reinforcement learning architecture for a mobile robot, where the individual components of the commanded velocity vector are learned in parallel by separate agents. We empirically demonstrate that the decentralized architecture outperforms its centralized counterpart using less computational resources. The method is validated on two problems: an extended version of the 3-dimensional mountain car, and a ball-pushing behavior performed with a differential-drive robot.

4 Developments and Changes for RoboCup 2016

4.1 New ball

A new ball is featured for the RoboCup 2016, a soft foam ball with a black and white soccer ball print. This change made considerably difficult the ball perception process. According to this change we have implemented a new method to identify the ball, in order to correctly track the ball position.

We search for white segments in our field of view, which are treated as ball spots candidates, several filters are applied over these segments, such as dimension, texture and border filters, in order to eliminate false positives and detect the ball.

4.2 Obstacle Map

In order to keep improving our performance, we have changed how we identify and keep track of obstacles, now using Random Finite Sets (RFS) (see section 3.1).

4.3 Iterative Closest Point

An Iterative Closest Point (ICP) algorithm was implemented to complement the Unscented Particle Filter in the estimation of the robot Pose. The combination of Unscented Particle Filter and Unscented Kalman Filter is used to estimate the pose when the difference between the estimated pose and the current pose is beneath a threshold. When the particle filter is unable to match any landmark or the difference between the estimated pose and the current pose is larger than the threshold, ICP is used to move the worst particle of the particle filter to a new estimated pose given by a linear Kalman filter of successive ICP pose estimatations. Then, if for this estimated pose the particle filter is able to match the observed and expected landmarks correctly, the filter is then expected to converge to this pose.

4.4 Vision Update

We are currently working on a automatic color (cube) calibration to provide a calibration-free vision system robust against change in lightning conditions and against shadows. To accomplish this, we based our work on previous work published by team HTWK[9], in which the YCbCr color cube is estimated using features based on image statistics and an ANN. To train this ANN we created a image database with different lightning conditions on our lab which is then used with the CMA-ES optimization algorithm to train the ANN weights. Finally, we use a statistic classifier to select which images modifies the cube to both improve results and avoid creating a cube based on non-informative or ill-conditioned images.

4.5 Behaviour Changes

We have changed how our behaviour works in a role level. Role Swapping has made several conflicts while playing, mainly causing undesired collisions between robots. Adressing this issue, we now treat certain roles as skills instead, which activates on robots coordinately, depending on the gameplay state.

5 Current Research Lines

Reinforcement Learning This line of work is part of the doctoral thesis of one of the team members. It is proposed to generate a methodology for implementing a decision making system, defining a state space according to specific game configurations, taking into account positions and probable team actions, and training recurrent and relevant game situations.

This work includes three main stages: *i)* the implementation or learning of tasks such as dribbling, intercepting the ball, kicking, going to strategic positions, and other similar basic behaviors; *ii)* the identification of specific game settings, and recurrent and relevant playing situations; *iii)* the reinforcement learning of high level behaviors based on a state-space transformation according to an specific game setting.

Interactive Machine Learning This line of work is part of the doctoral thesis of one of the team members. It is proposed to develop strategies for maximizing the information subtracted from the human feedback signals, in frameworks of Interactive Machine Learning wherein a person works as a teacher. It could be in paradigms either of Learning from Demonstrations (LfD) [4][3], in which the feedback is in the actions domain, or of IRL [11][16], in which the human feedback is in the evaluative domain. Some soccer robotics problems are being part of the sets of tested problems for evaluating all the proposals.

Humanoid biped gait This line of work is also part of the doctoral thesis of one of the team members. It is proposed to develop a methodology for designing a humanoid biped gait based on Dynamic Movement Primitives (DMP)[10, 15], developing a robust walking adaptive to some physical robot conditions (gear wear, encoders offsets, etc.). The trajectory generation are performed by using DMP instead of analytical models based on inverted pendulum or ZMP, trying to minimize its extensive required parametrization. The base leg trajectories are learned by imitation from other already implemented gaits and optimized with reinforcement learning. Because this initial knowledge taken from imitation, it is possible to reduce the number of epochs. So, it is able to implement reinforcement learning process in a real robot maximizing exploitation over exploration.

Visual Self-Localization This research line is part of a current master thesis, inspired by several works in Visual SLAM and Visual Odometry presented the last years, such as ORB-SLAM [14], LSD-SLAM[1] and SVO [8]. We are working towards a visual localization system independent of artificial landmarks that allows a NAO robot to localize in any place. In contrast to previous works in the RoboCup [2, 13], this is based on faster algorithms with open source code, in a similar way to [7]. We expect to present this approach applied to NAO robots soon.

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