UChile Robotics Team

Team Research Report - Robocup 2016

This document consists of both the contributions and the research topics of the UChile Robotics Team (UChileRT) for the RoboCup 2016. Section 1 presents the contributions made and shared to the community via open source code, and section 2 comprehends the research topics used on the team code for the RoboCup 2016.

1 Open Source Contribution

Tutorial - ROS Cross-Compiling and Installation for the NAO V4: UChileRT has uploaded to the ROS community, a detailed tutorial to build, install and run ROS natively onto the NAO V4 [11]. To the best on our knowledge, this was the first tutorial that provides a step-by-step guide to build, install and run ROS embedded onto the Atom CPU of the latest NAO V4 robot.

ROS Node - Motion Module: Currently, UChile Robotics Team is using the B-Human walking and motion engine [7]. That motion module has been isolated, integrated as a ROS node, and shared as open source code. It is described in [10].

New Ball Perceptor: The ball was updated for the the RoboCup 2016, as such, the team had to update the ball perceptor to comply with the needs. UChileRT has uploaded a repository with the used code[15], along a wiki document that contains useful information about the algorithmn and usage.

2 Research Lines for RoboCup 2016

2.1 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.

2.2 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 [9][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.

2.3 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)[8, 14], developing a robust gait, adaptive to certain physical robot conditions (gear wear, encoders offsets, etc.). The trajectory generation is 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 of other already implemented gaits and optimized with reinforcement learning. Since this initial knowledge comes from imitation, it is possible to reduce the number of epochs, thus, being able maximize exploitation over exploration while implementing reinforcement learning on a real robot.

2.4 Visual Self-Localization

This research line is part of a current master thesis, inspired by several works in Visual SLAM and Visual Odometry presented over the last years, such as ORB-SLAM [13], LSD-SLAM[1] and SVO [6]. 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, 12], this is based on faster algorithms with open source code, in a similar way to [5]. We expect to present this approach applied to NAO robots soon.

References

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