NimbRo SPL
German Open 2010 Team Description

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Abstract. This document describes the RoboCup SPL team NimbRo of Rheinische Friedrich-Wilhelms-Universität Bonn, Germany, for the RoboCup German Open competition to be held in Magdeburg in April 2010.
Our team won several competitions in the Humanoid KidSize and TeenSize class. To demonstrate that this success can be attributed to software and not to hardware, NimbRo participates for the first time in the SPL. The paper describes the NimbRo software used for perception and behavior control, which we want to transfer to the Nao robots. We also give an outlook to ongoing research.

1 Introduction

Our team NimbRo develops humanoid soccer robots since 2004. So far, we competed in the Humanoid League TeenSize and KidSize classes, where we won eleven international tournaments:

- RoboCup 2009: Winner TeenSize
- German Open 2009: Winner Humanoid League
- RoboCup 2008: Winner KidSize, third place TeenSize
- German Open 2008: Winner Humanoid League
- RoboCup 2007: Winner KidSize, Winner TeenSize
- German Open 2007: Winner Humanoid League
- RoboCup 2006: Winner Penalty Kick KidSize, second Soccer KidSize, second Penalty Kick TeenSize
- Dutch Open 2006: Winner Humanoid League
- RoboCup 2005: Winner Penalty Kick TeenSize, second Soccer KidSize
- German Open 2005: Winner Humanoid League

To demonstrate that this success can be attributed to software and not to hardware, NimbRo would like to participate in the SPL 2010.

This paper describes the NimbRo software used for perception and behavior control, which we want to transfer to the Nao robots. We also give an outlook to ongoing research.

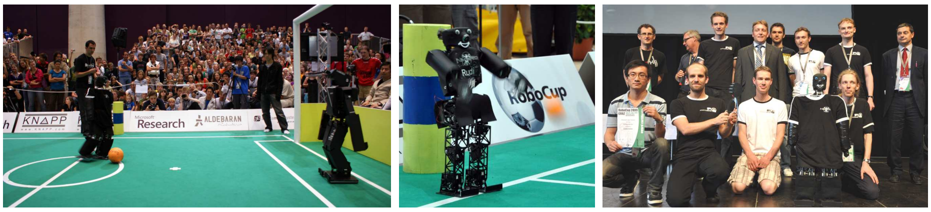

Fig. 1. At RoboCup 2009, our team won the Humanoid League TeenSize competitions.

2 Perception

The NimbRo robots are equipped with a high-performance perception system, which consists of proprioception and computer vision.

2.1 Proprioception

The readings of accelerometers and gyros are fused to estimate the robot's tilt. The gyro bias is automatically calibrated and the low-frequency components of the tilt estimated from the accelerometers are combined with the integrated turning rates to yield an estimate of the robot's attitude that is insensitive to short linear accelerations.

2.2 Computer Vision

We capture and process YUV images. Each pixel is color-classified in a fast multistage process using a color look-up table. In the downsampled color-classified image we detect the ball [12], the goals, the poles, goal-posts, penalty markers, field line features, obstacles, team mates, and opponents by color and size. We estimate distance and angle to each feature in the robot's egocentric coordinate frame by removing radial lens distortion and by inverting the projective mapping from field to image plane. For field line features at corners and T-junctions, we also estimate their orientation relative to the robot.

Behavior control moves the camera to keep the ball within the field-of-view or to look into the walking direction. This active vision strategy effectively increases the field-of-view of the robot.

We estimate the robot's pose on the field by filtering uncertain motion information and landmark observations in a probabilistic way. As the goals, the poles, and the goal posts are not sufficient for our localization purposes, we use landmarks like field line corners and field line T-junctions in addition. We use a Monte Carlo localization (MCL) approach, as it can represent multi-modal pose beliefs and can cope with unknown data association. In MCL, the estimate of the current pose of the robot based on previous observations and motion information, $p(s_t|z_{1:t}, u_{1:t})$, is represented with a set of weighted particles. At each time step, the estimate is updated recursively with new motion information and landmark observations. This recursive Bayesian filter is implemented with the Sampling-Importance-Resampling method.

To handle unknown data association of unidentified landmarks in MCL, we sample the data association c_t on a per-particle basis. It indicates the ID of the landmark to which the observation z_t corresponds. For each particle, we sample the association with a likelihood proportionally to the observation likelihood for the landmark in the particle's pose $s_t^{[i]}$, i.e. $c_t \sim \eta\ p(z_t|c_t, s_t^{[i]})$. Further details can be found in [15, 11].

3 Behavior Control

We control the robots using a framework that supports a hierarchy of reactive behaviors [4, 6, 5]. This framework allows for structured behavior engineering. Multiple layers that run on different time scales contain behaviors of different complexity. When moving up the hierarchy, the speed of sensors, behaviors, and actuators decreases. At the same time, they become more abstract. The framework forces the behavior engineers to define abstract sensors that are aggregated from faster, more basic sensors. Abstract actuators give higher-level behaviors the possibility to configure lower layers in order to eventually influence the state of the world.

The control hierarchy of our robots is arranged in an agent hierarchy, where
– multiple joints (e.g. left knee) constitute a body part (e.g. left leg),
– multiple body parts constitute a player (e.g. field player), and
– multiple players constitute a team.

In this hierarchy, we implemented:
– basic skills (e.g. omnidirectional walking [2, 3], kicking, getting-up behaviors)
– soccer behaviors (e.g. searching the ball, positioning behind the ball), and
– tactics and team behaviors (e.g. role assignment, player positioning)

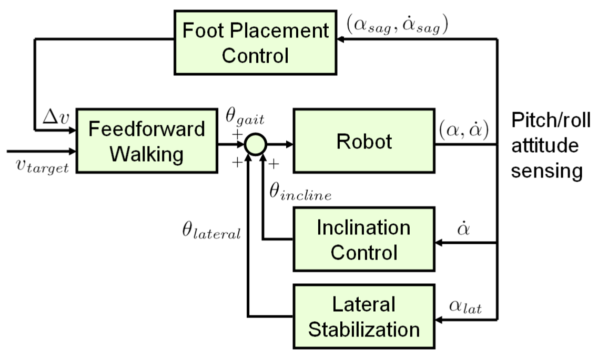

Fig. 2. Sketch of the feedback mechanisms used to stabilize omnidirectional walking.

We use feedback as sketched in Fig. 2 to increase the robustness of the gait against disturbances. This also increases usable gait velocities. The robots handle small disturbances by controlling the foot inclination according to the tilting rate of the trunk of the robot. To compensate larger tilts and tilting rates in the sagittal plane, we implemented a foot placement controller that modulates the sagittal walking velocity to 'catch up' with the tilt. We stabilize the lateral weight shifting by adjusting the lateral leg angles proportionally to the lateral tilt. We used stochastic gradient learning to optimize the parameters of the gait and of feedback mechanisms [13, 7].

These feedback mechanisms significantly improve the robustness of our gait. Hence, the feedback mechanisms are effective means to avoid falls. Falls cannot be prevented completely though. Our robots detect gait instabilities and try to prevent damage by landing in a controlled way [10]. We also developed strategies for ball prediction and quick ball capture for our goalie [16]. After a fall, our robots get up quickly [14].

4 Research Plan

For RoboCup 2010, we are currently conduction research in three directions:

1. We are incorporating more feedback into the generation of the walking patterns in order to reject larger disturbances. This includes the use of foot-contact sensors to adjust the timing of the gait, starting from the phase reset mechanism described in our previous work [7].
2. We are extending the hierarchical reactive control architecture to include hierarchical planning. By planning a constant number of actions on each behavior layer, we will be able to generate with high update rates long-term plans which are detailed in the near future and coarser in the longer future. We applied a similar technique with great success to accelerate path planning in dynamic environments [1].
3. We are combining reinforcement learning techniques with imitation learning in order to learn robot motions in a data-efficient way. We applied a similar technique before for scoring with soccer robots [9] and for grasping movements [8].

5 Conclusion

The success of our team NimbRo in the Humanoid KidSize and TeenSize class is a solid basis for participation in the RoboCup SPL. By porting the NimbRo software to the Nao robots, we hope to advance the state-of-the-art in the SPL. The most recent information about our team (including videos) can be found on our web pages www.NimbRo.net.

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