RoboCup 2012 Best Humanoid Award Winner NimbRo TeenSize

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Abstract. Over the past few years, soccer-playing humanoid robots advanced significantly. Elementary skills, such as bipedal walking, visual perception, and collision avoidance have matured enough to allow for dynamic and exciting games. In this paper, team NimbRo TeenSize, the winner of the RoboCup 2012 Best Humanoid Award, presents its robotic platform and its approaches to perception and behavior control.

1 Introduction

In the RoboCup Humanoid League, mostly self-constructed robots with a human-like body plan compete with each other. The league comprises three size classes: KidSize (<60 cm), TeenSize (90–120 cm), and AdultSize (>130 cm). The TeenSize robots started to play 2 vs. 2 soccer games in 2010 and moved to a larger soccer field of 9×6 m in the year 2011. This year, a 3 vs. 3 demonstration game showed that –in principle– TeenSize robots are ready to play soccer the way it is done in the KidSize class, given enough participating teams and robots. In addition to the soccer games, the robots face technical challenges, such as throwing the ball into the field from a side line.

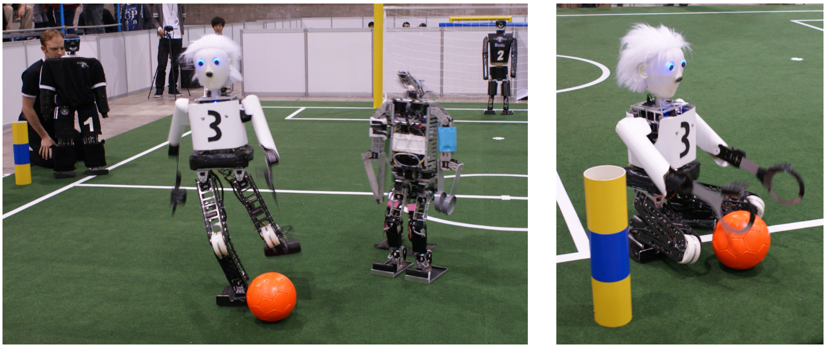

Fig. 1. Left: NimbRo robots Dynaped, Copedo, and Bodo playing in the 3 vs. 3 demo game. Right: Copedo performing the ThrowIn Challenge.

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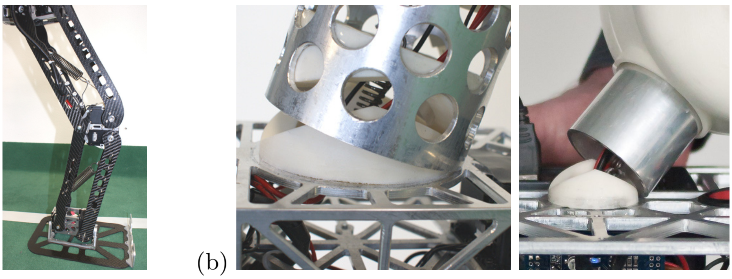
Team NimbRo has a long and successful history in RoboCup with overall ten wins in international Humanoid League competitions since 2005. In 2012, our team won the TeenSize competition for the fourth time in a row and completed the Technical Challenge with the maximum possible score. We have been awarded the Louis Vuitton Best Humanoid Cup for the second time.

2 Mechatronic Design of NimbRo TeenSize Robots

The mechatronic design of our robots, which are shown in Fig.1, is focused on robustness, weight reduction, and simplicity.

Copedo: Our main innovation for the RoboCup competition this year was the construction of a new TeenSize robot that we named "Copedo" (Figure 1). Copedo is 114 cm tall and weighs 8 kg. Its body plan is derived from its successor Dynaped, including the 5-DOF legs with parallel kinematics (Fig. 2(a)) and the spring-loaded passive joint between the hip and the spine (Fig. 2(b)). Copedo, however, is equipped with an additional protective joint in the neck to protect the head. Our new generation of protective joints is now able to snap back into position automatically after being displaced by mechanical stress, such that the robot remains operational after falling to the ground and does not need to be set manually. Copedo is constructed from milled carbon fiber parts that are assembled to rectangular shaped legs and flat arms. The torso is constructed entirely from aluminum and consists of a cylindric tube that contains the hip-spine spring and a rectangular cage that holds the information processing devices.

Most importantly, Copedo is equipped with 3-DOF arms that include elbow joints to enable the robot to get up from the ground and to pick up the ball from the floor and to throw it (Figure 1, right). Including a neck joint to pan the head, Copedo has 17 actuated DOF. The hip roll, hip pitch, and knee DOF are actuated by master-slave pairs of Dynamixel EX-106+ servo motors. All other DOF are driven by single motors including EX-106+ motors for ankle roll, EX-106 motors for hip yaw and shoulder pitch, RX-64 motors for shoulder roll and elbow, and an RX-28 motor for the neck yaw joint.



(a) (b)

Fig. 2. Mechanical construction of Copedo: (a) leg with parallel kinematics; (b) spring-loaded overload protection in the hip and the neck joint

3 Perception

For visual perception of the game situation, we process 752×480 YUV images from a IDS uEye camera with fish eye lens. We detect the ball, goal-posts, poles, penalty markers, field lines, corners, T-junctions, X-crossings, obstacles, team mates, and opponents utilizing color, size and shape information. We estimate distance and angle to each detected object by removing radial lens distortion and by inverting the projective mapping from field to image plane. To account for camera pose changes during walking, we learned a direct mapping from the IMU readings to offsets in the image.

For proprioception, we use the joint angle feedback of the servos and apply it to the kinematic robot model using forward kinematics. Before extracting the location and the velocity of the center of mass, we rotate the kinematic model around the current support foot such that the attitude of the trunk matches the angle we measured with the IMU. Temperatures and voltages are also monitored for notification of overheating or low batteries.

For localization, we track a three-dimensional robot pose (x, y, θ) on the field using a particle filter [1]. The particles are updated using a linear motion model. Its parameters are learned from motion capture data [2]. The weights of the particles are updated according to a probabilistic model of landmark observations (distance and angle) that accounts for measurement noise. To handle unknown data association of ambiguous landmarks, we sample the data association on a per-particle basis. The association of field line corner and T-junction observations is simplified using the orientation of these landmarks. Further details can be found in [3] and [4].

Learning Colors of Unknown Balls: This year, for the first time, the robots had to learn to recognize an unknown ball in the Obstacle Avoidance and Dribbling Challenge. To this end, we defined a region of interest in the field-of-view of the robot, which contained only the field color (green carpet) and the unknown ball (Fig. 3(a)). In this area, we segmented all colors different from the field color, white, and black (Fig. 3(b)). The remaining color histograms were thresholded with a minimum color count and smoothed. We fitted a Gaussian mixture model to the colors of the unknown ball and used its parameters to initialize the ball color in our color table (Fig. 3(c)). Dynaped was the only TeenSize robot to complete this challenge (Fig. 3(d)).

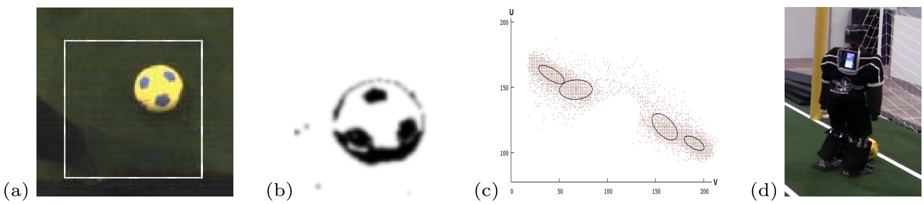


Fig. 3. Ball learning: (a) region of interest with unknown ball; (b) segmented pixels; (c) UV color histogram; (d) Dynaped completing the Dribbling Challenge

4 Behavior Control

We control our robots using a layered framework that supports a hierarchy of reactive behaviors [5]. When moving up the hierarchy, the update frequency of sensors, behaviors, and actuators decreases, while the abstraction level increases. Currently, our implementation consists of three layers. The lowest, fastest layer is responsible for generating motions, such as walking—including capture steps [6], kicking, and the goalie dive. At the next higher layer, we model the robot as a simple holonomic point mass that is controlled with the force field method to generate ball approach trajectories, ball dribbling sequences, and to implement obstacle avoidance. The topmost layer of our framework takes care of team behavior, game tactics and the implementation of the game states as commanded by the referee box. Please refer to [4] for further details.

Get-up Motion: We designed get-up motions for Copedo using a simple, linear interpolated keyframe technique [7]. The motions are executed open-loop after a prone or supine position has been detected. The challenge of performing a get-up motion with parallel kinematics, and thus missing a degree of freedom to pitch the foot, is that the robot is not able to explicitly place its foot flat on the ground. Using its arms, the robot pushes itself up from the floor while retracting its legs and rotating around the front or the back edge of the foot. When the center of mass crosses this edge, the robot will inevitably start tilting quickly towards the other side, pass the pose where the foot is flat on the ground with a relatively high rotational velocity, and is in danger of tipping over again. We found that holding the legs not fully retracted combined with some servo compliance results in a springy leg behavior that quickly dampens the back and forth rocking on the foot edges. Using this technique, active balancing is not required. Once the robot has reached a stable squatting position with the feet flat on the ground, it only has to stretch its legs to regain a standing posture and can continue walking. The get-up motions are illustrated in Figure 4.

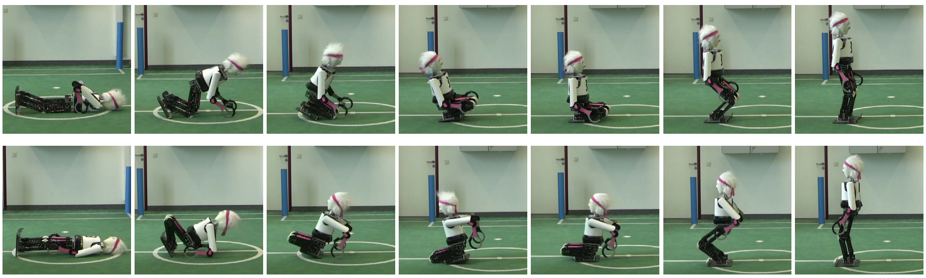


Fig. 4. Top row: Get-up motion from the prone posture. Bottom row: Get-up motion from the supine posture. In both motion sequences, the robot passively rocks back and forth on the foot edges from frames 3 to 5.

5 Conclusions

The 2012 competition showed notable progress in the development of the TeenSize class. Four participating teams were able to play dynamic soccer games and to complete several technical challenges. The highlights this year were the 3 vs. 3 demo game, where six goals were scored, and an exceptionally exciting final game between team NimbRo (Germany) and CIT Brains (Japan). The Japanese team was able to gain a lead in the first half with a surprisingly aggressive strategy. After a tie of 2:2 at half time, NimbRo played more offensively in the second half and achieved a final score of 6:3 for NimbRo.

In the future, the Humanoid League will continue to raise the bar. In the next year, equally colored goals will force the teams to deal with completely symmetric landmarks for localization and new technical challenges will require more sophisticated sensomotoric skills.

In order to make it easier for other teams to participate in the TeenSize class, our team NimbRo developed a modular open TeenSize robot platform, which will be released open-source and which will be made available to other teams for an affordable price [8].

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