

# The UPennalizers

## RoboCup Standard Platform League

### Team Description Paper 2018

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**Abstract.** The UPennalizers is a robocup standard platform team from the University of Pennsylvania. This paper presents the most recent research projects and accomplishments by the team UPennalizers in preparation for the RoboCup 2018 in Montreal, Canada.

**Keywords:** RoboCup, SPL, 2018, University of Pennsylvania

## 1 Introduction

The UPennalizers is affiliated with the General Robotics, Automation, Sensing and Perception (GRASP) Laboratory and the School of Engineering and Applied Science at the University of Pennsylvania. In 1999, two years after the first international RoboCup, this robot soccer team was formed and began to step up to the challenges put forth by the competition. While the league was still utilizing four-legged Sony Aibos, the UPennalizers became the runner-up in 2003 and made to the quarter-final rounds every year through 2006. After taking a brief two-year hiatus in 2007, the team was reformed and returned in 2009 to begin competing in the Standard Platform League with humanoid robots NAO, taking on bipedal motion alongside improved vision techniques and advanced behavior planning. We believe robotics competition is a great way to demonstrate scientific and engineering solutions in practical settings and also to connect robotics research with broader audiences. In May 2018, the UPennalizers hosted the RoboCup US Open at the University of Pennsylvania.

Supervised by Professor.Daniel Lee, the 2018 team consists of Xiang Deng (team leader), Daniel Pak, Fiona La, Alamelu Thinnappan, Ryan Walsh, and Abdullah Zaini. Figure 1 shows team members at the RoboCup US Open 2018.

This paper is organized as follows. Section 2 introduces an overview of our software system. Section 3 describes our recent work in perception including ball detection and adaptive color classification in different lighting environments. Section 4 provides our recent progresses in velocity generation for enhanced stability and convergence to desired goal poses. Section 5 presents our redeveloped locomotion pipeline and recent accomplishments in motions. Section 6 concludes with directions for future work.

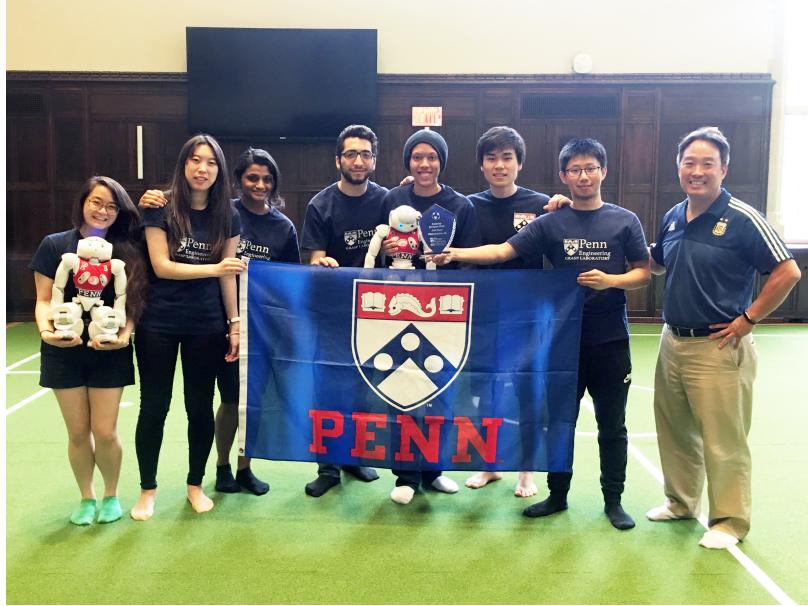


Fig. 1: The UPennalizers team at the RoboCup US Open 2018 in Philadelphia, USA. From left to right: Fiona La, Jiyong Cho, Alamelu Thinnappan, Abdullah Zaini, Ryan Walsh, Daniel Pak, Xiang Deng and Prof. Daniel D. Lee.

## 2 System Overview

The current software system of the UPennalizers integrates perception, locomotion and behavior modules together in an efficient, scalable and cross-platform way to enable a team of robots to play autonomous soccer. The perception module handles object detection routines, recognizing the soccer ball and field features which are further utilized for localization. The locomotion engine allows omni-directional walk and uses sensory feedback to compensate for external disturbances. High-level behavior module uses finite state machines to define single robot's behavior as well as the team strategy. The overall structure of our software architecture is shown in Figure 2. Our software runs on the Linux operating system and is written in a combination of Lua and C/C++. The C/C++ routines implement the low level processing, handling interactions to motors and sensors systems in Naoqi, along with our kinematics and image processing libraries. The Lua portions interact with C/C++ device driver routines, operating the high-level vision and locomotion processes and behavior state machine. Those high-level routines are platform agnostic which could be easily plugged into different humanoid and simulation platforms [2]. We also use MATLAB for external monitoring and debugging. Detailed descriptions of our software system can be found in the previous team reports [3] [4] .

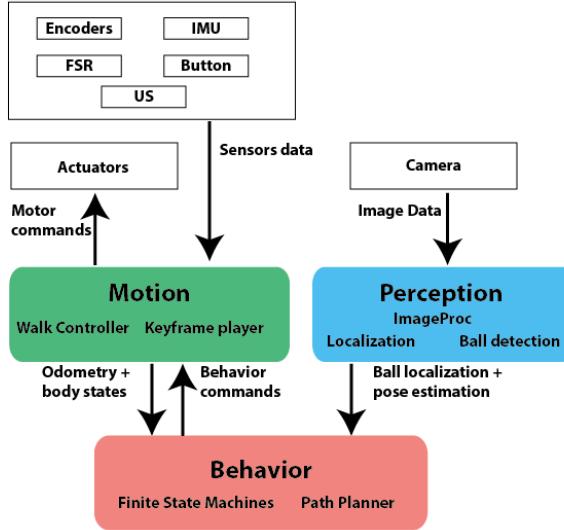


Fig. 2: Block Diagram of the Software Architecture

### 3 Perception

#### 3.1 Ball Detection

In previous years, our teams ball detection was performed mainly by analyzing the properties of segmented pixels. Although this approach worked well in an open field, it failed when the ball was overlapping with another white object in the image frame, such as lines, goal posts, and robot feet. The ball-on-line scenario was cleverly solved using properties of black blobs, but such a work-around had limitations of being restricted to very specific situations. Additionally, natural lighting conditions make black color segmentation much more challenging, which makes approaches that rely on perfect color segmentation much less reliable.

Our current approach is to propose regions that would likely contain the ball and classify them with a binary classifier. For region proposal, we are using a feature map in YCbCr colorspace that makes two important assumptions [1]. First is that the ball is on a green field, and second is that the ball is at a fixed height (i.e. on the floor). Using the property that green color has low Cb and Cr values, we take the average of the two channels and compare the sum of those values inside two bounding boxes - one that tightly fits the ball, and one that is offset to include the region outside the ball (Fig. 1a). The bounding box that tightly fits the ball is calculated using coordinate transformation and the assumption that the ball is at the robots foot level. If the region inside has a

much higher Cb+Cr value per pixel than the region outside, then the center of the region receives a high score on the heat map (Fig. 1c). After the heat map is created, we find the locations of local maxima and define the bounding box with that center as the proposed region.

After successful region proposal, we need to classify each region as ball or not ball. For US open Robocup 2018, we used heuristics with color segmented pixels, which either limited possible ball detection scenarios on the top camera or resulted in false positives. For Robocup 2018, we are developing a convolutional neural network (CNN) binary classifier, which may solve these issues.

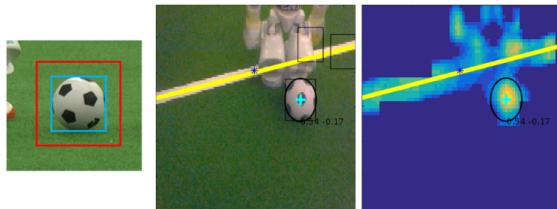


Fig. 3: (a) Feature map, (b) original image, and (c) heat map

### 3.2 Lighting Invariant Color Classification

In preparation for the lighting challenges at RoboCup 2018, we are developing algorithms that can adapt our perception techniques e.g. line detection and localization from static lighting environments to natural lighting conditions. Enhancing the robustness of color segmentation i.e. green and white colors labeling under different lighting conditions i.e. dark, bright, or uneven lightings has been one of our major focuses.

Until US open RoboCup 2018, our approach of real-time and accurate field green and white color classification was based on color tables. Unfortunately, the color table method we had developed was only suitable for static lighting environments and required hand-labeling of colors and re-training of look up tables for the specific environment before each game.

Our new approach of lighting invariant color classification aims to adapt pre-trained color tables on-site. Interpreting lighting changes from the known environments by extracting luminance features from a given image is the key. Based on comparisons of luminance features, we then adapt the color tables which predicts the green and white colors in a given image. Fig. 4, Fig. 5 and Fig. 6 show probabilistic heat maps of green and white color predictions for a same environment under different lighting: bright, dark, and uneven lights, using our current algorithm with same default parameters.

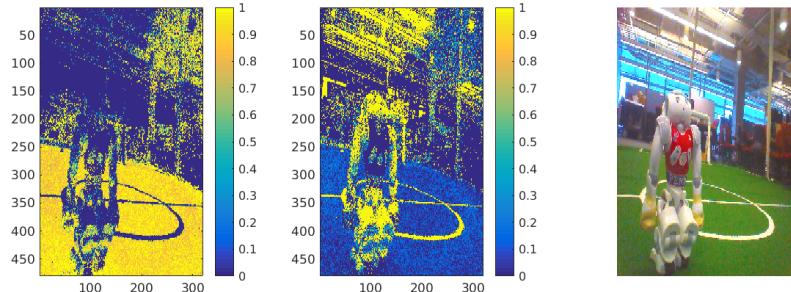


Fig. 4: (a) Heat map showing the confidence of field green prediction; (b) heat map of white color prediction; (c) original image taken under bright lighting.

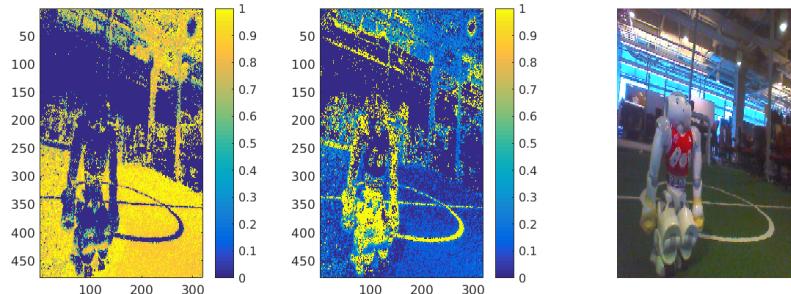


Fig. 5: (a) Probabilistic heat map of field green prediction; (b) heat map of white color prediction; (c) original image taken under dark lighting.

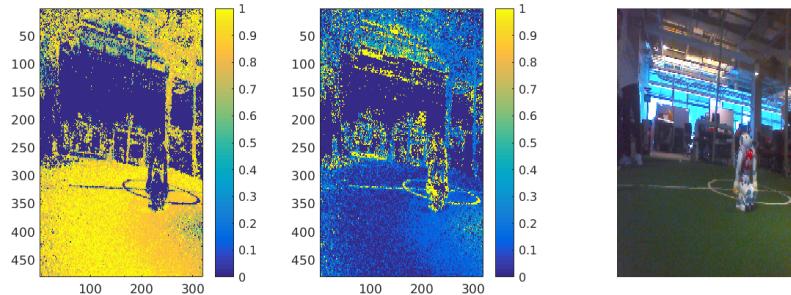


Fig. 6: (a) Probabilistic heat map of field green prediction; (b) heat map of white color prediction; (c) original image taken under uneven lighting.

## 4 Behavior

### 4.1 Velocity Generation Strategy

In previous years, velocity generation that relied solely on position and heading errors caused instability and path divergence when localization or ball measurements were noisy. Moreover, velocities generated by previous methods occasionally commanded incompatible sets of conflicting translational and rotational velocities that would cause bizarre motions such as facing forward but walking backwards with the head turned.

We have re-developed our velocity generation which is now based on a finite state machine that recognizes six distinct states a robot can be in when approaching a target pose. When a new target pose is selected, the relative distance and angle are used to determine the appropriate initial state. Each of the four initial states begin a different path to reach the final state, where the target pose is reached and all velocity values are zero. The finite state machine enforces sequential sets of velocities that will converge at the target pose. The proposed solution further increases stability by restricting the sequence and combinations of velocities, ensuring the robot will face the ball when reasonably possible. Furthermore, contrasted with traditional path planning methods, such as A\* or rapidly-exploring random trees (RRT), the simplicity of this method reduces complexity an important consideration for the computationally limit platform of the NAOs.

Table 1 describes the entry conditions for the initial states. In addition, figure 7 illustrates a diagram of the state machine with the velocity commands for each state and table 2 describes each of the transition conditions labeled in figure 7.

	<b>Entry Condition</b>
<b>State 1</b>	Current pose is close to target position
<b>State 2</b>	Current pose is a moderate distance away from target pose and target pose faces away from robot
<b>State 3</b>	Current pose is a moderate distance away from target pose and target pose faces towards robot
<b>State 4</b>	Current pose is far from target position

Table 1: Entry conditions for each of the four initial states.

## 5 Locomotion

Our research in locomotion focuses on the foundations in kinematics and dynamics for humanoid robot locomotion and for kick, squat, dive and get-up motions.

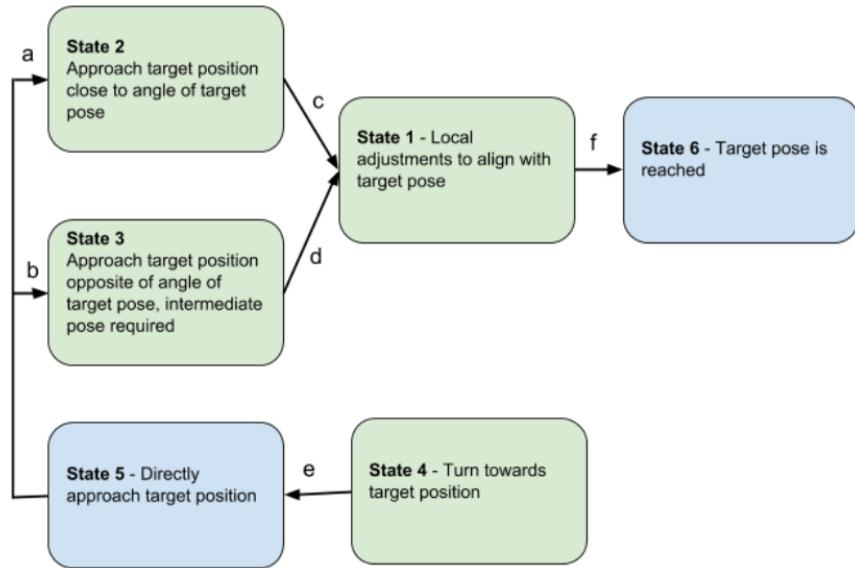


Fig. 7: Overview of each of the states in the finite state machine, transitions are labeled a - f. Initial states are highlighted in green.

	<b>From</b>	<b>To</b>	<b>Transition condition</b>
<b>a</b>	5	2	When the current position is a moderate distance away from target position and the target pose faces away from robot
<b>b</b>	5	3	When the current position is a moderate distance away from target position and the target pose faces towards robot
<b>c</b>	2	1	When the current position is close to the target position
<b>d</b>	3	1	When the current position is close to the target position
<b>e</b>	4	5	When the current pose faces the direction of the target position
<b>f</b>	1	6	When the current pose aligns with the target pose

Table 2: Description of all transition conditions in the finite state machine.

### 5.1 Walk Controller

In 2018, we have redeveloped our walk control pipeline which now integrates adaptive foot step control and torso regulation using sensory feedback. Figure 8 shows an overview of the most up-to-date walk controller pipeline. The main goal of the new pipeline is to breakthrough the limitations of our walk controller before 2018 which heavily relied on trajectory tracking and was more likely to fail due to external disturbances and motor noises.

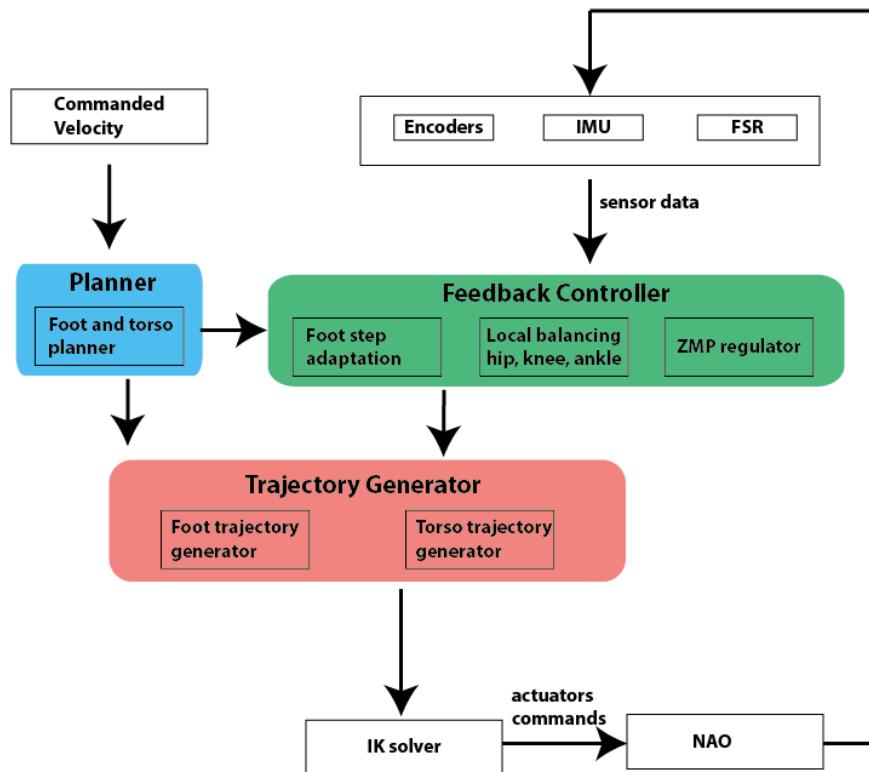


Fig. 8: Overview of the walk controller 2018

### 5.2 Dynamically Stabilized Walk-Kick

During the tournaments of RoboCup 2017, we developed a dynamically stabilized walk-kick, which demonstrated robustness during the games. We continued improving this module since 2017. Figure 9 best describes our walk-kick which is essentially in a combination of kick-and-balance motions incorporated in the walking controller.

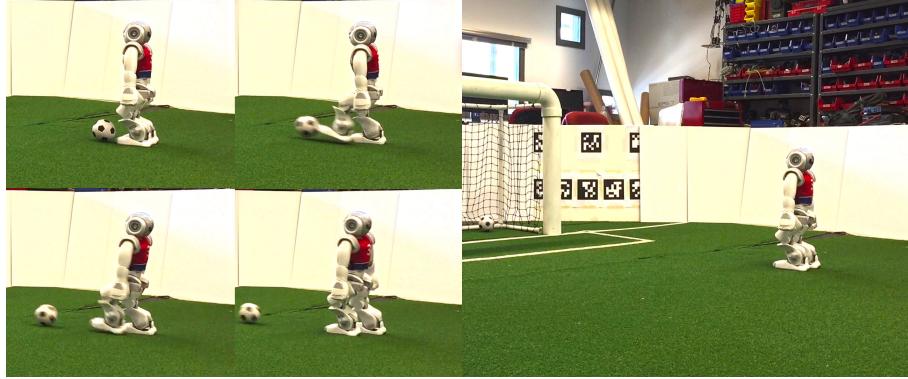


Fig. 9: Walk kick and stabilization

### 5.3 Computational Tools for Key-frame Motions



Fig. 10: Goal keeper squad and stand up motions

We are in the progress of developing a computational driven approach to discover and/or improve key-frame based motions under constraints. For example, figure 10 shows our new goal keeper's squad then stand up motions. For this sequence of motions, our goal was to achieve a balance among blocking area, time of stand-up and safety (we prefer the robot not to instantaneously sit on the ground in order to prevent damages).

## 6 Conclusions and Future Work

The paper describes the UPennalizer's most recent research in vision, behavior, and locomotion in preparation for the RoboCup competitions in 2018. Our team will need to continuously test, challenge and improve the robustness of our software and to make sure the newly developed modules in vision, behavior and locomotion integrate well on a system level.

## 7 Acknowledgment

We thank the GRASP Laboratory and the School of Engineering and Applied Science at the University of Pennsylvania. We would also like to thank all former team members for their contributions to the team developments in the past.

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