Learning a Kick while Walking in Raw Actuator Space

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Abstract

Many walk and kick behaviors in the RoboCup 3D soccer simulation went through learning optimization (e.g. [1; 2]). Deep learning approaches tend to work on raw data. In this paper we make a first step towards generating raw output data by learning a kick behavior in joint space. The number of free parameters is above 100. Optimization included pure genetic algorithms and CMA-ES. The achieved kick is a 5m kick that can be performed while running at 0.8m/s.

1 Approach

Creating raw data for each joint would mean to create 50 values per second for each of the 24 joints of the Nao with toes. As a first step, we limited the search space to the leg joints only. Also, instead of creating 50 values per second, we make use of the fact that output values of a joint over time are not independent. Therefore, we create the joint angles for four distinct phases of movement together with the angular speeds the joints should have producing picewise linear functions. In addition, the duration of each phase is learned as well as the distance to the ball in which we want to trigger the behavior. This adds to 117 parameters for learning.

2 Results

The overall result of the learning process is shown in Figure 1. It was achieved using a plain genetic algorithm with population size = 100, genders = 2, parents per individuum = 2, individuum mutation probability = 0.1, gene mutation probability = 0.1, elite selection, multi-crossover recombination. Utility function is the kick width (positive x-coordinate). The Figure shows the fitness of all individuums with 4-fold oversampling, the average and the maximum fitness. CMA-ES produced slightly weaker results in terms of best fitness, though using less calculation time.

Figure 2 shows the fitness of the best individuum starting from different start positions kicking always with the right leg. Each value is the average of 10 kicks. Two things are noteworthy: first, the kick learned when approaching the ball straight does not work very well, when approaching from an angle. Second, without step planning, some distances do not workout well, when the distance does not fit the step size. This can easily be improved by also allowing the left leg to kick.

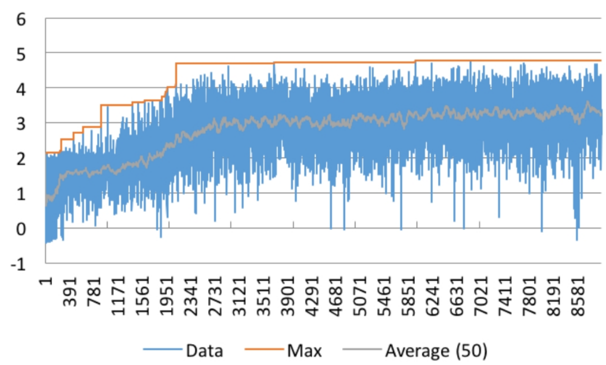

Figure 1: Average and maximum utility over time.

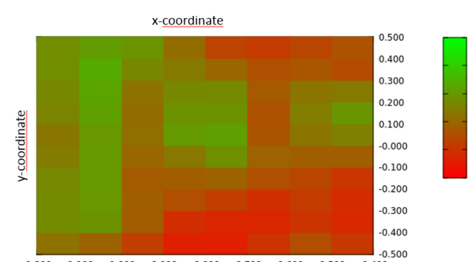

Figure 2: Evaluation of different start positions.

References

[1] Abdolmaleki A, Simoes D, Lau N, Reis L P, Neumann G: *Learning a Humanoid Kick With Controlled Distance.* To appear, 2016.

[2] MacAlpine P, Depinet M, Stone P: *UT Austin Villa 2014: RoboCup 3D Simulation League Champion via Overlapping Layered Learning.* Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI), vol 4, pp. 2842–48, 2015.