# Fast, Human-Like Running and Sprinting 

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#### Abstract

Automated learning of skills from scratch is becoming a desirable technique, given the available machine learning tools and the ever-increasing computational speed. Reinforcement learning approaches can obtain state-of-the-art results, while employing model-free algorithms without prior knowledge of the task at hands. This method is particularly useful in the RoboCup 3D Soccer Simulation League, for which the optimization process can be directly accomplished in Simspark. One of the most relevant low-level skills in this league is concerned with the robots locomotion. The major flaw in current approaches is linear speed, followed by rotational speed. Dominating theses fields can give a serious advantage over the opponent [1,2].

Two main skills were developed - run and sprint. The former allows the robot to turn to any direction while running. It is composed of a main action and two subtasks which allow the robot to stop or progressively shift to walking. The latter skill is more focused on speed and less on turning, and, due to its flexible nature, it can end with a ball kick, in addition to stopping or shifting to walking. Both behaviors control all the NAO's joints except for the head.

The behavior was learned using an adapted Proximal Policy Optimization (PPO) strategy - a model-free reinforcement learning algorithm. The optimization was performed for 200M time steps using the SimSpark simulator. Table I shows relevant statistics for the most successful robot types. The displayed values for the main skills were averaged over 1000 episodes of 10 seconds each.


Table 1. Sprinting and Running results

| Skill | Avg. \& Max. linear speed along $x$ | Max. rot. speed | Subtask | Duration |
| :---: | :---: | :---: | :---: | :---: |
| Sprint | $2.48 \mathrm{~m} / \mathrm{s} \& 2.62 \mathrm{~m} / \mathrm{s} \$$ | $10^{\circ} / \mathrm{s}$ | Walk Transition | $0.9 s$ |
|  |  |  | Stop | $[1,1.8] s$ |
| Run | $1.41 \mathrm{~m} / \mathrm{s} \& 1.52 \mathrm{~m} / \mathrm{s}$ | $160^{\circ} / \mathrm{s}$ | Walk Transition | $0.9 s$ |
|  |  |  | Stop | $[1,1.6] s$ |
|  |  |  | Kick | N.A. |

The fastest sprinter (type 2) achieves an average linear speed of $2.48 \mathrm{~m} / \mathrm{s}$ from the initial standing position until the episodes end. The top speed stabilizes at around $2.62 \mathrm{~m} / \mathrm{s}$. The best performing runner (type 4 ) is able to run in a straight line up to $1.52 \mathrm{~m} / \mathrm{s}$ and then rotate to any direction at a maximum of $160^{\circ} / \mathrm{s}$. Sprinting and running can transition into walking smoothly in 45 time steps (equivalent to 0.9 s ). To bring the robot to a stationary position, it takes between 1 s and 1.8 s , depending on the gait phase. Fig. 1 shows a sequence of frames taken from the sprinting behavior at different cycles of the running gait. The robots motion follows a human-like pattern, and actively uses its arms to stabilize itself.


Figure 1. Sample figure caption.

## References

[1] Abreu, M., Reis, L. P., \& Lau, N. (2019, July). Learning to run faster in a humanoid robot soccer environment through reinforcement learning. In RoboCup 2019: Robot World Cup XXIII. Springer. (to appear)
[2] Abreu, M., Lau, N., Sousa, A., \& Reis, L. P. (2019, April). Learning low level skills from scratch for humanoid robot soccer using deep reinforcement learning. In 2019 IEEE Intern. Conf. on Auton. Robot Systems and Competitions (pp. 1-8). IEEE.

