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Online Learning of Sagittal Push Recovery for Bipedal Robots

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Bipedal walking is a complex and dynamic whole-body motion with balance constraints. Due to the inherently unstable inverted pendulum-like dynamics of walking, the design of a robust walking controller proves to be particularly challenging. While a controller could potentially be learned with a robot in the loop, the destructive nature of losing balance and the impracticality of a high number of repetitions render most existing learning methods unsuitable for an online learning setting with real hardware.

We propose a model-driven learning method that enables a humanoid robot to quickly learn how to maintain its balance. We bootstrap the learning process with a Central Pattern Generator (CPG) for stepping motions that abstracts from the complexity of the walking motion and simplifies the problem setting to the learning of a small number of leg swing amplitude parameters. A simple physical model that represents the dominant dynamics of bipedal walking estimates an approximate gradient and suggests how to modify the swing amplitude to restore balance. In experiments with a real robot, we show that only a few failed steps are sufficient for our biped to learn strong push recovery skills in the sagittal direction.

The architecture of our learning gait controller is illustrated in Fig. 1. A bipedal robot (bottom right) is a part of the control loop. It receives joint target positions $\boldsymbol{q}$ from the control software and provides joint angles $\hat{\boldsymbol{q}}$, accelerometer data $\hat{\boldsymbol{a}}$, and gyroscope data $\hat{\boldsymbol{\omega}}$. Stepping motions are generated with the periodic motion signals of a CPG (top right) [1]. The CPG exhibits a parameter vector $\boldsymbol{A} = (A_x, A_y, A_\psi)$ that contains dimensionless activation signals to control the leg swing amplitudes in the sagittal, lateral, and rotational directions. In the State Estimation module (bottom left), we estimate the trunk angle $\boldsymbol{\theta} = (\theta_x, \theta_y)$ and angular velocity $\dot{\boldsymbol{\theta}}$ in the pitch and roll directions and reconstruct the tilted whole-body pose of the robot using the measured joint angles $\hat{\boldsymbol{q}}$. In the moment of the support exchange, we obtain the step size estimate $\boldsymbol{S}_E$ by computing the distance between the feet, and the end-of-step trunk angle $\boldsymbol{\theta}_E$. These two quantities are used to train the gait controller. A higher instance controls the gait of the robot by commanding a step size $\check{\boldsymbol{S}}$. This parameter is illustrated as an input to the Balance Control module (top left). The Balance Control has the task of obeying the commanded step size while maintaining the balance of the biped. The Balance Control function $\boldsymbol{A} = \boldsymbol{\mathcal{B}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \check{\boldsymbol{S}})$ computes the leg swing amplitude

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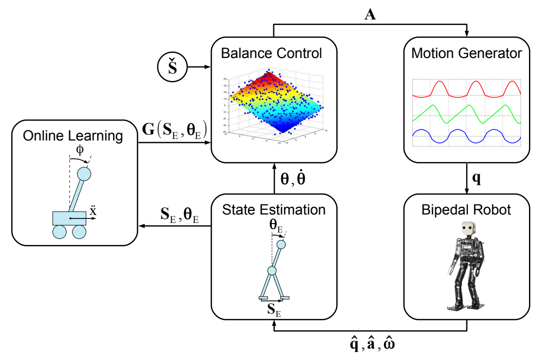

Fig. 1. The architecture of our learning gait controller.

activation vector $\boldsymbol{A}$ for the CPG as a function of the trunk angle $\boldsymbol{\theta}$ and angular velocity $\dot{\boldsymbol{\theta}}$, and the desired step size $\check{\boldsymbol{S}}$. We represent the sagittal component of the Balance Control function $\mathcal{B}_x$ with a function approximator [2] and initialize it with a zero output. At the end of each step, we compute a step size gradient $\boldsymbol{\mathcal{G}}(\boldsymbol{\theta}_E, \boldsymbol{S}_E)$ with the help of the pole-cart model and train the Balance Control function approximator with the update rule

$$\mathcal{B}_x(\theta_{y_i}, \dot{\theta}_{yi}, \check{S}_x) := \mathcal{B}_x(\theta_{y_i}, \dot{\theta}_{yi}, \check{S}_x) + \eta\, \mathcal{G}_x(\theta_{Ey}, \bar{S}_x), \forall i \in I, \tag{1}$$

where η is a learning rate, I is an index set, and $\{\theta_{y_i}, \dot{\theta}_{yi}\}, i \in I$ is the set of trunk pitch angles and angular velocities that were measured during the step. After only a few pushes, we obtained one of the strongest bipedal push recovery skills to date (see Fig. 2).

References

[1] M. Missura and S. Behnke. Self-Stable Omnidirectional Walking with Compliant Joints. In *Workshop on Humanoid Soccer Robots*, Atlanta, USA, 2013.

[2] S. Vijayakumar, A. D'souza, and S. Schaal. Incremental online learning in high dimensions. *Neural Comput.*, 17(12):2602–2634, December 2005.

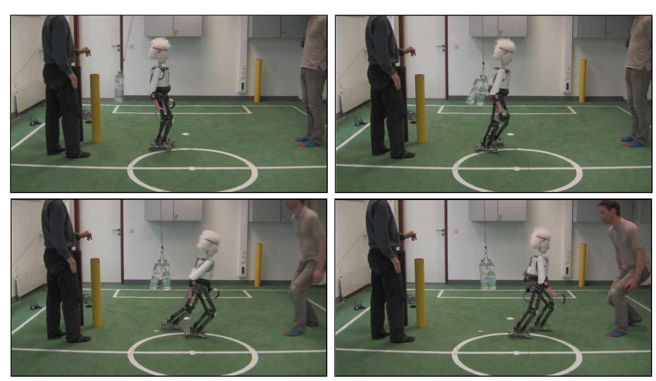

Fig. 2. Humanoid robot Copedo regains its balance after a strong push from the back. Video: `http://youtu.be/qeWjy36gCBU`