Safe trajectory optimization for whole-body motion of humanoids

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I. INTRODUCTION

The generation of complex whole-body movements for humanoid robots typically involves the definition of a set of tasks (*i.e.*, tracking a desired trajectory for the joints or the end-effectors, either positions or forces), performance objectives (*e.g.*, minimize the torques), under a set of constraints (*e.g.*, joint limits, motors limits) that assure that the motion is physically feasible on the real robot. For example, let us consider a stand up from a chair motion for a humanoid robot. This motion, trivial for a human, is very challenging for a humanoid. Guaranteeing the safety of the desired trajectory plays a premiere part in a context where human-humanoid interaction is involved. Safe motion generation requires that the robot will perform the global task while satisfying constraints on the feasibility of the final motion like mechanical range, limitations stemming from the interaction with the environment and conservation of the balance.

Although the research community has converged to a consensus framework to solve this multi-task, multi-constraint problem (see [1] [2]), typically this framework requires a great amount of manual tuning and when it is formulated as a Quadratic Programming (QP) problem, it may not guarantee that the final solutions will satisfy all the constraints (due to relaxation).

In this paper we adopt the opposite approach followed in our previous work [3]. Instead of automatically learning the task priorities while keeping the tasks fixed, here we resolve to adopt a predefined blending strategy for the tasks and optimize the desired task trajectories.

II. METHOD

Given a balance and a posture task, in this work we propose a framework that learns the optimal values of a parametrized Center of Mass (CoM) trajectory in the sagittal plane represented as a Radial Basis Functions (RBFs) network. The balance torque controller of [4] tracks the desired task trajectory sending joint torque commands to the robot. In order to learn the trajectory parameters we repeat the experiments numerous times in simulation. At the end of each rollout we feed the resulting fitness to an instance of (1+1)CMA-ES with Covariance Constrained

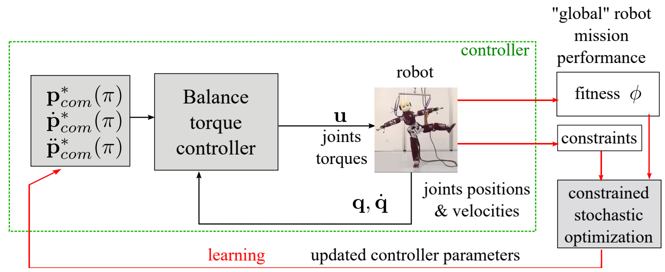

Fig. 1: Overview of the proposed method. The balance controller executes a desired task trajectory, represented by a parametrized function. An outer learning loop enables the optimization of the parameters of the task trajectory, taking into account the constraint violations in an explicit way.

Adaption (CCA) to find an optimal solution that satisfies the experiment constraints. The integration of the learning module with an established feedback torque controller lets us obtain solutions that are robust and that can be easily extended to multi-contact scenarios. In Figure 1 a scheme that outlines our method is presented.

III. RESULTS AND FUTURE WORK

We test our method in a simulation of a “stand-up from the chair” task, to find an optimal CoM trajectory for an iCub humanoid. The results show that the trajectories computed with our method are safe and produce better results in terms of energy consumption and task satisfaction than a hand-tuned one. Realizing this kind of motion was not possible in our previous framework where task priorities were optimized.

In order to improve the framework’s resilience against disturbances and modeling errors, in the future we plan to leverage transferability approaches for deploying and refining the solution directly on the real robot. More specifically we plan to apply a modified version of the ”Intelligent Trial and Error” approach [5], that performs an extensive search of the parameter space to find multiple optimal solutions and selects the one that has the best performances on the hardware.

REFERENCES

[1] A. D. Prete, F. Nori, G. Metta, and L. Natale, “Prioritized motion force control of constrained fully-actuated robots: atask space inverse dynamics,” *Rob. and Auton. Systems*, vol. 63, pp. 150 – 157, 2015.
[2] M. Liu, Y. Tan, and V. Padois, “Generalized hierarchical control,” *Autonomous Robots*, vol. 40, no. 1, pp. 17–31, Jan 2016.
[3] V. Modugno, U. Chervet, G. Oriolo, and S. Ivaldi, “Learning soft task priorities for safe control of humanoid robots with constrained stochastic optimization,” in *HUMANOIDS*, 2016.
[4] D. Pucci, F. Romano, S. Traversaro, and F. Nori, “Highly dynamic balancing via force control,” in *HUMANOIDS*, 2016, pp. 141–141.
[5] A. Cully, J. Clune, D. Tarapore, and J.-B. Mouret, “Robots that can adapt like animals,” *Nature*, vol. 521, no. 7553, pp. 503–507, 2015.

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