Geodesic trajectory generation on learnt skill manifolds

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1 Motivation

Humanoid robots are appealing due to their inherent dexterity. However, their potential benefits may only be realized with a correspondingly flexible motion synthesis procedure. Designing flexible skill representations that also capture non-trivial dynamics effects over a large domain, such as in real humanoid robots, has been an open challenge. This poster presents one such flexible trajectory generation algorithm that utilizes a geometrical representation of humanoid skills (e.g., walking) - in the form of skill manifolds [1]. Such manifolds are learnt from demonstration data that may be obtained from off-line optimization algorithms (or a human expert). This model may be used to produce approximately optimal motion plans (that capture constraints and dynamics implicit in the output of a computationally expensive off-line optimization procedure) as geodesics over a manifold and this allows us to effectively generalize from a limited training set. We demonstrate the effectiveness of our approach on a physical 19-DoF humanoid robot, exhibiting fast motion planning on a realistic – variable step length, width and height – walking task.

2 Implementation

Central to our approach is a nonlinear manifold learning method that is able to capture the geometrical properties of the intrinsic low-dimensional manifold that training data points are generated from. Our learning algorithm is a modification of LSML by Dollar et al. [2], which we have adapted with robot motion-specific issues in mind. Formally our goal is to learn a model of the tangent space of the low-dimensional nonlinear manifold, conditioned on the adjacency relations of the high dimensional data. The learnt manifold yields geodesic distances, projections of points on the manifold and allows us to directly generate optimal geodesic paths between points. Our approach captures the continuum of solutions both inside and outside (within a neighbourhood) the support of the original data. We demonstrate that such paths are approximately optimal with respect to the initial – ground truth – optimality criteria and planning is suitably fast.

3 Experimental Setup

We have used the *KHR-1HV* (Fig. 1(c)), a 19 DoF humanoid robot. We focus on the task of walking, with the aim of generating a motion synthesis strategy that allows for full coverage of a reasonably large interval in step length, height and width. For generating demonstration data we have framed the redundancy resolution strategy as an unconstrained nonlinear optimization problem. We have used a Quasi-Newton approach with a cubic line search procedure, that uses the BFGS formula for iteratively updating the estimate of the Hessian of the objective (cost) function. The cost function we have defined is a mixture of task constraints and stability constraints. We have separated each footstep to a swing phase and a weight shift phase. This way we have divided learning into two components, a leg swing manifold and support weight shift manifold, as the measure of optimality is essentially different for each phase.

4 Results

The learnt manifolds are able to produce smooth walking trajectories that satisfy the optimization criteria used to produce the training data. Specifically, the average *RMSE* of the leg swing manifold was as low as 0.12 while the average *RMSE* of the weight shift manifold ranged on average near 0.06 (Fig. 1(e)). The procedure was able to produce stable walking in the continuum of the reaching space of the robot as depicted in Fig. 1(a) and 1(d) for right and left swings accordingly. A random walk entirely generated with our method is depicted in Fig. 1(f). Notice that the step lengths are varying and the step points are variable as well with respect to the x axis. Snapshots of this walk executed by the robot are shown in Fig. 2. We demonstrate how a manifold learning algorithm can capture the geometric properties of a low-dimensional skill-specific manifold, that underlies a high dimensional dataset, and how to *tightly integrate this* with the process of trajectory generation. This model can be naturally used to generate joint space trajectories that reflect the optimality and constraints inherent in the training data, thus producing novel approximately optimal solutions to continuous path planning queries efficiently.

References

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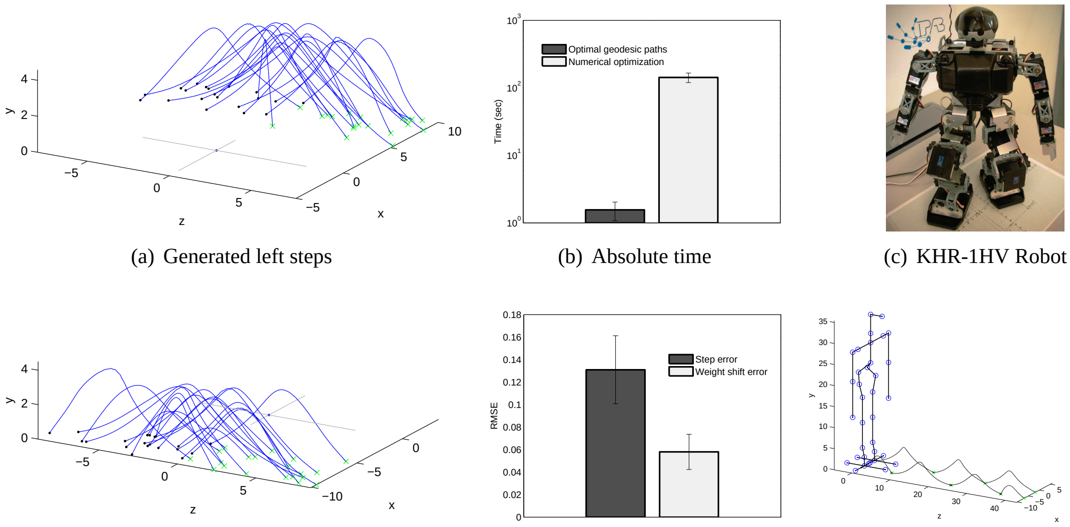
[2] P. Dollár, V. Rabaud, and S. Belongie, “Non-isometric manifold learning: Analysis and an algorithm,” in *ICML*, June 2007.



(a) Generated left steps (b) Absolute time (c) KHR-1HV Robot

(d) Generated right steps (e) Error (f) Generated random walk

Figure 1: Experimental results with the humanoid robot (c). Random start and end point trajectories for left (d) and right (a) leg swings that have been generated from our learnt manifold, via geodesic path optimization. (b) absolute time needed for planning and optimization with our method and the nonlinear optimization method (y axis in logscale). (e) *RMSE* of generated data against ground truth. (f) Random walk generated by geodesic path optimization on the learnt manifolds for randomized task-space goals. Snapshots of the robot executing the motion in Fig. 2.

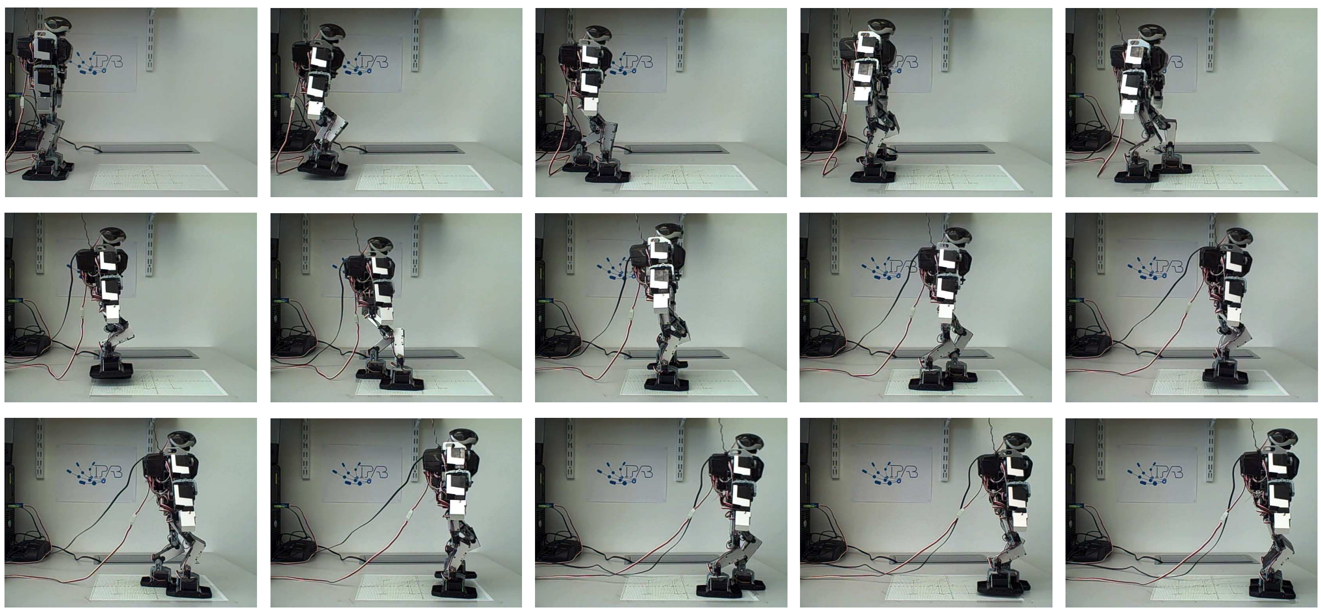


Figure 2: Stills of the robot executing the planned motion depicted in Fig. 1(f).