Obstacle Climbing with a Humanoid Robot guided by Human Demonstrations

Pavan Kanajar[1], Darwin G. Caldwell[1] and Petar Kormushev[2]

***Abstract*— Humanoids can explore the environment not only through bipedal locomotion but they could also operate like quadrupeds when trying to scale challenging obstacles. The ability to change from bipedal to quadruped locomotion could help humanoid robots to significantly expand the reachable space to include large obstacles and navigate in disaster situations. We present an enhanced version of our previously proposed multi-contact motion planner. The approach is validated on a humanoid robot COMAN with a multi-contact task involving climbing of a large wooden obstacle. Our multi-contact motion planner is initialized with a human demonstration of the task. Limited-memory BFGS (L-BFGS) optimization is used by our multi-contact planner to adapt the demonstrations over contact and static stability costs to make it suitable for the humanoid robot COMAN. Multi-contact solutions are generated using QP formulation along with adaption of priorities of the internal Cartesian tasks for the humanoid robot.**

I. Introduction

Humanoid research on non-periodic locomotion advanced relatively slowly in the past decade. However, in the recent years the state-of-the-art has improved mainly through research on movement synthesis and character animation for the performance of various actions like getting up, walking, doing handstands etc. [1], and motion planning for climbing stairs with hand supports using analysis of various ladder climbing strategies [2].

For traditional bipedal robot walking the state of the art has advanced rapidly, but, the main focus is on balancing the robot via foot stepping [3] on flat or even terrains. These bipedal walking robots try to avoid any other external contact with the obstacles in the surrounding environment. In this work, we want the humanoid robot to make external contacts with the environment, to gain additional support, to improve locomotion in even/uneven terrains. This capacity to deal with all terrains will make humanoids much more helpful in physical assistance scenarios or disaster response situations.

In the DARPA disaster response finals, most of the humanoid robots failed at some point even with humans-in-the-loop throughout the process. Although the final challenge course was a human centered environment, none of the humanoids tried to take due advantage of their surroundings and many robots fell due to loss of balance while using only their feet to maintain balance.

[1]Department of Advanced Robotics, Istituto Italiano di Tecnologia, Via Morego 30, 16163 Genova, Italy. pavan.kanajar@iit.it

[2]Robot Intelligence Lab, Dyson School of Design Engineering, Imperial College London, South Kensington, London SW7 2AZ, UK. p.kormushev@imperial.ac.uk

The approach we use here contains four major steps: demo of the task and demo sequence tagging, multi-contact optimization using our algorithm and finally motion planning with open loop control on the humanoid robot COMAN. Generally a global planner using A* search algorithm along with heuristics or RRT planning are used for contact planning in humanoid robots. Here we perform a human demonstration of the task, which gives us a proper strategy for a particular task.

Our multi-contact motion planning algorithm uses the demonstration sequence to train an initial set of contacts for the robot links to interact with the obstacle. This also clearly specifies the goal of the task for our planner. Then our algorithm optimizes these contacts to find stable contact points over the obstacle.

II. Demonstrations via Optical Tracking

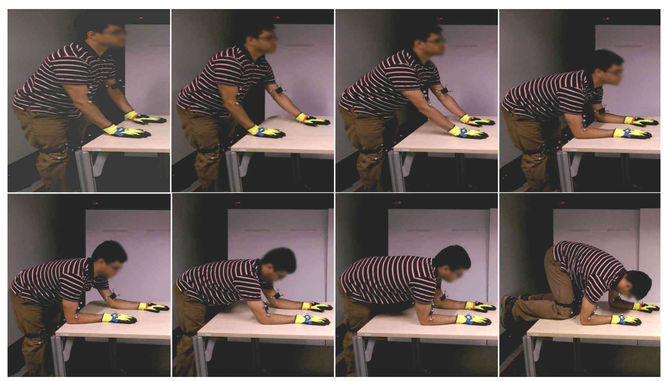

Fig. 1: The demonstration of climbing a table at different contact stages in a series of snapshots. The demonstrator shows good enough number of intermediate steps to climb over the table.

A demonstration of climbing the table (used as an obstacle) is performed by the demonstrator. The table's height is adjusted to a height, $h = 0.65\ m$ such that the person can easily use both his arms and legs to climb on the table. We use this demonstration to devise a multi-contact strategy to overcome obstacles with full-body motions.

Optical markers are used along with an OptiTrack motion capture system for tracking the marked individual parts in the cartesian space during the task demonstration as shown in Fig. 2. Optimal markers are used at places close to both left and right knees, wrists, elbows and also one on the obstacle to note the relative reference for the positions recorded. We use the tracked position and orientation data to extract the contact plan for the task along with contact references to aid as an initial reference for the climbing task. Optical markers data are used to get the contact reference position, orientation and sequence of contact placements. At each new contact step during the demonstration, a mouse click is used to acknowledge a newly made contact has occurred. The process of tagging data, discretizes the recorded movements into different contact stages as shown in Fig. 3. These contact references are as initialization reference for our multi-contact motion planning algorithm.

III. Multi-Contact Motion Planning Algorithm

The steps involved in the multi-contact motion planning algorithm are listed. The contact stages from the demonstrations shown in Fig. 1 are used as a initialization for the planner.

Input: Position references
Output: Stable contact postures
while *new position reference exists* **do**
  Initialization with next position references;
  Formulate cartesian task T using QP;
  Generate stable posture using common supporting links;
  Run the contact position optimizer;
  Solve for whole body inverse kinematic (IK);
end

Algorithm 1: Multi-contact Planning Algorithm

A. Cartesian Task Formulation

Given a Cartesian reference, we can design a task T defined by its Jacobian J and error e associated with it as

$$T = (J, e) \tag{1}$$

These tasks are solved with a Quadratic Programming (QP) formulation. In a humanoid robot we need multiple tasks for each kinematic chain like legs and arms. QP based OpenSoT control library allows such stacks of multiple tasks to solve for IK by concatenating task Jacobians $\begin{bmatrix} J_1^T & J_2^T \end{bmatrix}$ and their errors $\begin{bmatrix} e_1^T & e_2^T \end{bmatrix}$. Using the desired contact states from demo, we define such stack of Cartesian tasks and solve for contact reference inputs to generate whole body solutions for a humanoid robot. Further using hard prioritization for the tasks in stack, we define higher priorities for tasks related to the support links like legs. The priority table used during initial and final phases of the task is shown below.

Task Priority	1st Phase	2nd Phase
2	Legs	Arms
1	Arms	Legs

To guarantee stability at contacts in the robot legs, for example if we have contact at the left foot we can guarantee full stability if the projection of the left hip mass centroid is coincident at foot position. We do this for shoulder mass position if contact occurs at hands or elbows. We define our stability cost as norm of projection offset between the contact support link position and mass position, P_{offset} as,

$$|| \sum P_{offset} || \tag{2}$$

where the summation denotes sum of all support mass position offset when multiple links are providing support for the robot, which is optimized using L-BFGS optimization.

B. Multiple contact points in the same kinematic chain

We have instances of multiple contact requirements in a single kinematic chain. For example, in the fourth demonstrated contact stage in Fig. 3, both elbow J_1 and wrists J_2 which are parts of the arm kinematic chain are in contact with the table obstacle. The QP initialization to fails due to inconsistencies in the task definition, since the rank of the task Jacobian drops since we have common joints angles i.e.,

$$Rank(J_1^T) + Rank(J_2^T) < Rank(\begin{bmatrix} J_1^T & J_2^T \end{bmatrix}) \tag{4}$$

Instead of enforcing hard priorities, we combine these task with soft priorities to solve them together inside a single QP problem with Jacobian J_A as

$$J_A = \begin{bmatrix} W_1 J_1^T & W_2 J_2^T \end{bmatrix} \tag{5}$$

where W_1 and W_2 are weight diagonal matrices through which we define soft priorities for the tasks by setting their corresponding diagonal elements to a positive value. Our algorithm automatically chooses priorities using the following table to assign the soft priorities accordingly.

Precedence	Low		High
Kinematic chains			
Arms	Wrists	Elbows	Shoulders
Legs	Feet	Knees	Hips

For lower precedence contacts we choose a weight matrix with diagonal elements set to 0.1 and for higher precedence contacts we set them to 1.

IV. Conclusion

We have presented multi-contact motion planner for climbing obstacle with the humanoid robot COMAN from demonstration. The strategy was demonstrated via optical marker tracking to record the initialization of the planner. Our multi-contact motion-planner optimizes these references while ensuring stability and contact constraints to generate intermediate stable postures. These postures can be used further by a motion planner to generate solution for obstacle climbing with the humanoid robot COMAN.

References

[1] Igor Mordatch, Emanuel Todorov, and Zoran Popovic. 2012. Discovery of complex behaviors through contact-invariant optimization. ACM Trans. Graph. 31, 4, Article 43, July 2012.

[2] J. Luo et al., "Robust ladder-climbing with a humanoid robot with application to the DARPA Robotics Challenge," 2014 IEEE International Conference on Robotics and Automation (ICRA), Hong Kong, 2014.

[3] P. Kryczka, P. Kormushev, N. G. Tsagarakis and D. G. Caldwell, "Online regeneration of bipedal walking gait pattern optimizing footstep placement and timing," 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, 2015.