Humanlike Motion Planning

Marcelo Kallmann, Yazhou Huang, and Mentar Mahmudi

Abstract— **The problem of planning humanlike motions is difficult to define, to model and to solve. It is however a problem that will grow in importance as humanoid assistants and autonomous virtual characters become essential in many applications. In this abstract we propose simple definitions to model basic aspects of the problem and summarize algorithms based on multi-modality and search spaces defined from example motions.**

I. INTRODUCTION AND DEFINITIONS

Synthesizing whole-body humanoid motions with humanlike characteristics is a challenge. One first difficulty that arises is to define what makes a motion to be humanlike. A simple useful definition is proposed as follows:

Definition 1: a humanlike motion is a motion that, when closely performed by a human, looks familiar to several human observers.

The key element of Definition 1 is that humanlike motions look familiar to humans. Familiarity implies that humanlike motions have been previously observed in past situations, and that human observers can *understand* basic aspects of the motions, like type and intent. Motions that cannot be understood are not motions familiar to humans. Definition 1 allows humanlike motions to be observed in non-humans (as in humanoid robots) and makes no distinction to the quality of humanlike motions. For example, a happy walking motion is as humanlike as a sad or neutral walking motion.

Definition 2: a humanlike motion planning problem is the problem of computing a humanlike motion that solves a given task.

The problem of planning a humanlike motion starts with the goal of solving a specific task. Example of tasks are: grasping objects, pressing buttons, pointing to objects, pouring water, walking, etc. In realistic scenarios most of these tasks will involve whole-body motions with coordinated manipulation and locomotion (see Fig. 1). The resulting whole-body mobile manipulation problem is challenging and involves configuration spaces that are difficult to search with traditional methods due to the high dimensionality and the strong bipedal balance constraints. Furthermore, additional constraints in the configuration space have to be imposed for delimiting the subspace of humanlike motions, a problem that is still open and difficult to address.

The authors are with the School of Engineering of the University of California, Merced, N. Lake Road, Merced CA 95343. {mkallmann,yhuang6,mmahmudi}@ucmerced.edu

Given these many difficulties, two key elements emerge as essential to the development of a humanlike motion planner: multi-modality and example motions. Multi-modality allows to address whole-body problems per-skill, each being planned efficiently by dedicated planners. Example motions are useful to define and constrain search spaces to humanlike motions, ensuring that solutions look familiar and not awkward or like a surprise to human spectators.

Fig. 1. A typical humanlike motion planning problem involving precise end-effector placement in coordination with locomotion [1].

II. MULTI-MODALITY

The proposed approach starts by decomposing the problem into a multi-modal planning problem where basic skills are planned individually and also coordinated with each other. This approach is inspired by how humans may solve real motion planning problems and generic frameworks using multi-modal planning techniques can be devised [3].

Consider the task of planning a humanlike motion composed of two parts: locomotion for body positioning, and then upper-body action execution satisfying a given end-effector goal location p_g. The goal location may be a position target to point to, a 6 degrees of freedom vector encoding position and orientation of a precise hand placement for grasping, etc. The set Q_g denotes all possible body postures satisfying the action goal point p_g, and q_i represents the initial full-body posture of the humanoid.

The goal of the locomotion skill planner is to explore suitable body placements for enabling the action planner to reach a posture in Q_g. When the locomotion planner generates a

posture q_a that is close enough to p_g, q_a is then considered as a transition point to the upper body action and q_a becomes the initial posture for the upper-body action planner, which will in turn attempt to reach a posture in Q_g.

If the upper-body planner is not successful after a fixed number of iterations, the locomotion planner continues to expand towards additional candidate body placements until the action can be executed or until a maximum time limit is reached, in which case the overall planner returns failure. Fig. 2 illustrates the bi-modal overall search procedure, and a full description of the method is available in [1].
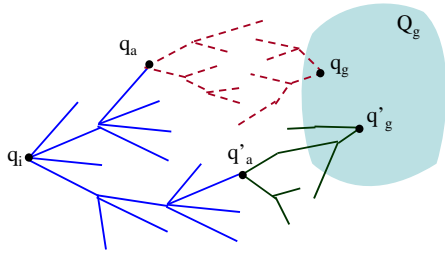

Fig. 2. Searching for transition points from locomotion to action execution. Here q_a was not able to generate a solution after a fixed maximum number of iterations and a new body placement q'_a was finally successful.

III. Efficient Path Planning with Clearance

In order to approach humanlike performances the described multi-modal planner has to be efficient. Clearly, a full locomotion planner is only needed nearby narrow passages or nearby the action execution location. In normal conditions 2D path planning coupled with steering algorithms should be enough for humanlike locomotion. Humans are very efficient at planning 2D paths in planar environments, a simple look ahead being sufficient to precisely determine a path to take with enough clearance among obstacles. An efficient algorithm for planning paths with clearance is therefore essential in humanlike motion planning.

The Local Clearance Triangulation introduced in [2] provides an exact cell decomposition of arbitrary planar environments, allowing exact and complete search algorithms to find paths of arbitrary clearance in optimal times (see Fig. 3).

IV. Action Planning in Blending Spaces

Definition 1 requires humanlike motions to be familiar to humans, a process that would require extensive interactive experiences with humans. A natural way to efficiently include such knowledge into a planning algorithm is to define search spaces from example motions captured from humans. In this way, humanlike upper-body actions can be modeled and specified with a database of similar and time-aligned example motions, which are upper-body action instances directly collected from motion capture. Given any set of blending weights, a new motion can be produced by blending the ones in the database.
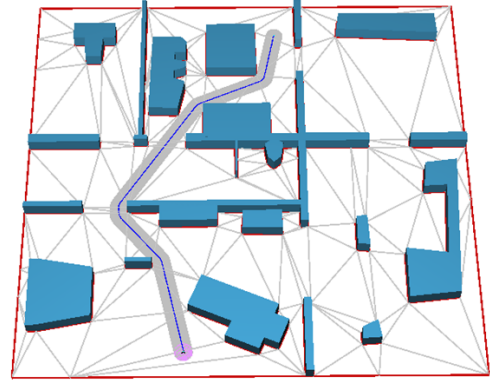

Fig. 3. Example of a Local Clearance Triangulation and a path of guaranteed clearance computed directly from the triangulated environment.

The action planner proposed in [1] searches in the continuous weight-temporal space of possible motion blendings in a database and is key for achieving humanlike results: it enables a search procedure that explores the motion variations available in the set of example actions. The planner will never synthesize new motions from scratch but instead will search for combinations of existing motion variations. The solution plan is a sequence of time parameterized blending weights that are afterwards interpolated to achieve a smooth solution motion with varying contributions from the example actions. See Fig. 4 for an example.

In a robotic platform, databases of example human motions could be dynamically updated and organized during interaction with humans as needed, supporting interactive humanlike learning and synthesis experiences.

Fig. 4. The solution of pointing over an obstacle is humanlike since it came from example motions in a database of humanlike pointings [1].

References

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