# Motion Planning of Human-Like Robots using Constrained Coordination

Liangjun Zhang  Jia Pan  Dinesh Manocha
{zlj,panj,dm}@cs.unc.edu
*Dept. of Computer Science, University of North Carolina at Chapel Hill*
*videos at http://gamma.cs.unc.edu/DHM*

***Abstract*— We present a whole-body motion planning algorithm for human-like robots. The planning problem is decomposed into a sequence of low-dimensional sub-problems. Our formulation is based on the fact that a human-like model is a tightly coupled system and we use a constrained coordination scheme to solve the sub-problems in an incremental manner. We also present a local path refinement algorithm to compute collision-free paths in tight spaces and satisfy the statically stable constraint on CoM. We demonstrate the performance of our algorithm on an articulated human-like model and generate efficient motion strategies in complex CAD models.**

## I. Introduction

The problem of modeling and simulating human-like motion arises in different applications, including humanoid robotics, biomechanics, digital human modeling for virtual prototyping, and character animations. One of the main goals in this area is to develop efficient motion strategies for whole-body planning for various tasks including navigation, sitting, walking, running, object manipulation, etc. The entire human body consists of over 600 muscles and over 200 bones, half of which are found in the hands and feet. Even the simplest human-like models represent the skeleton as an articulated model with $30-40$ joints to model the different motions. The underlying complexity makes it hard for a planner to efficiently compute the motion due to the dimension of the configuration space. In addition to collision-free constraints, the resulting motion also needs to satisfy the posture and dynamics constraints.

Recent research in robotics has focused on motion planning of humanoids due to the commercial availability of humanoid robot hardware [11], [20]. Many earlier approaches use a simple bounding volume (e.g. a cylinder) approximation of the entire human model [19] or the lower body [1], [26] to compute the collision-free motions, and design appropriate gaits or locomotion controllers to follow those trajectories [14], [16]. Recently there has been a trend of computing the motion for the whole body [13], [34]. However, most prior motion planning approaches are only efficient for open or simple environments and their performances may degrade in cluttered environments.

Besides humanoids, another driving application of human-like robots is digital modeling of humans or mannequins for design, assembly and maintenance in CAD/CAM and virtual prototyping [8], [21]. The digital human models can be inserted into a simulation or virtual environment to facilitate the prediction of performance, safety and ergonomic analysis of the CAD models. For example, human-like models are used in validating vehicle or aircraft designs to ensure that there will be sufficient clearance in the CAD model for a human operator to remove a complex part. In order to perform these tasks, we need to develop capabilities for complex motion strategies (e.g. sitting, bending), handling narrow passages, and planning in cluttered environments.

One approach to solve high DOF planning problems is to decompose a problem into a set of lower dimensional sub-problems [1], [2], [15]. For instance, a human-like robot can be decomposed into the lower body and the upper body. In order to deal with CAD/CAM applications, we need to handle cluttered environments and model many other motions, which cannot be efficiently generated by simple decompositions. In addition to collision-free constraints, the motion of human-like robots is subject to statically or dynamically stable constraints. There is a general perception that actual human motion results from simultaneously performing multiple objectives in a hierarchical manner, and researchers have developed similar models for dynamics control [29]. It would also be useful to develop approaches that use hierarchical decompositions for planning human-like motions.

**Main Results:** We present a whole-body motion planning approach for human-like robots by coordinating the motions of different body parts. Our approach performs a hierarchical decomposition and takes into account that a human body is a tightly coupled system.

- We describe a new constrained coordination scheme that uses constrained sampling and incrementally computes the motion for different parts, satisfying collision-free constraint.
- In order to deal with cluttered or tight scenarios, we present a local path refinement algorithm that takes into account the workspace distance information to control the amount of modification on the path.
- We modify statically unstable samples by using inverse kinematics (IK) so that the new samples are statically stable with respect to the center of mass of the robot.

We demonstrate the performance of our algorithm on an articulated human-like model with 40 DOF. We generate various motion strategies corresponding to bending, standing-up, and grabbing objects in different complex scenarios. In practice, our planner is able to compute a collision-free and statically stable motion in tens of seconds. Within a two-stage framework which first computes a collision-free path then transforms the path to a dynamically stable trajectory

(Fig. 2), our approach can improve the efficiency of the first stage.

The rest of the paper is organized as follows. We give a brief survey of related work in Section II and an overview of our decomposition approach in Section III. Section IV presents the constrained coordination algorithm as well as local path refinement. We describe our implementation in Section V and highlight its performance.

## II. Previous Work

There is an extensive literature on motion planning, coordination and dynamic control of human-like robots. In this section, we give a brief overview of related work on motion planning for human-like robots, dimensionality reduction and path replanning.

### A. Motion Planning for Human-Like Robots

Sampling-based approaches have been successfully applied to human-like robots to plan various tasks. These include efficient planning algorithms for reaching and manipulation that combine motion planning and inverse kinematics [6], [7] or computing the whole body motion [13]. The motion strategies for human-like robots such as walking can also be computed by using walking pattern generators [14], [16], [18]. To plan collision-free and dynamically stable motions, many previous approaches use a decoupled two-stage framework (Fig. 2) [12], [20], [35]. Task-based controllers have also been presented to plan and control the whole-body motion [11], [29]. In the domain of computer animation, motion capture data are often used to synthesize natural human motion [32].

### B. Dimensionality Reduction

Decomposition techniques can reduce the overall dimensionality of motion planning problems and have been applied to articulated robots or multi-robot systems [2], [15]. Different coordination schemes for combining the solutions of lower dimensional sub-problems are presented in [9], [23], [28]. Simple decomposition schemes based on the lower-body and upper-body can be used for planing the motion of human-like robots [1]. Another effective scheme for dimensionality reduction is to use reduced kinematic models, such as using a bounding cylinder to approximate the lower body [19], [26]. A multi-level method to adjust the activated DOF according to the environment is presented in [34]. Finally, PCA-based analysis or various task constraints can also be used to guide the sampling towards the lower dimensional space [5], [30].

### C. Path Modification and Replanning

The step of path modification is often required by many motion planning approaches. Retraction-based sampling approaches can effectively deal with narrow passages and cluttered environments [4], [36]. By performing random perturbation or penetration depth computation, a path with colliding configurations can be repaired. For motion planning among dynamic obstacles, local path modification algorithms

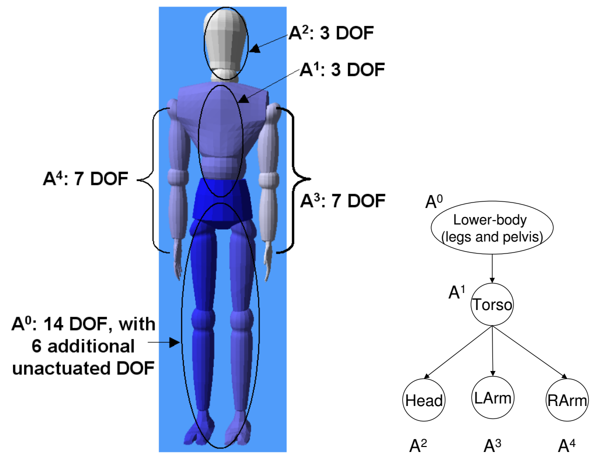



Fig. 1. *A human-like robot with* 40 *DOF and one decomposition scheme for this model. Our approach computes the motion for the body parts sequentially by starting from the root of the hierarchy of the decomposition.*

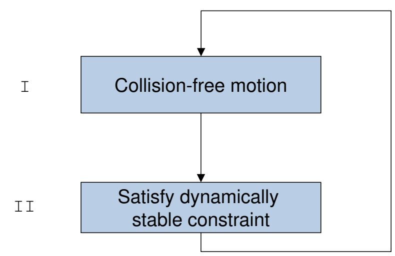



Fig. 2. *Within the decoupled two-stage framework for planning a motion satisfying with both collision-free and dynamically stable constraints, our approach can improve the efficiency of the stage I: collision-free and statically stable motion computation.*

modify the portion of the path to avoid the moving obstacle or to accommodate changes in the connectivity [27], [33]. Since global modification needs to replan for the entire connectivity map, it is usually much more expensive [10], [17].

## III. Overview

In this section, we introduce our notation and give an overview of our planning algorithm. Planning a path for a human-like robot by taking into account all the DOF is often difficult due to the underlying high dimensional search space. Our approach represents a human-like robot by using a set of body parts, i.e. $\{A^0, A^1, ..., A^n\}$. We decompose the problem into multiple sub-problems of lower dimensions, and compute the motion for the body parts in a sequential order. A key feature of our algorithm is that planning the path of the $k^{th}$ body part is coordinated with the paths of the first $k-1$ body parts computed earlier. Furthermore, all these paths can be refined using a local refinement scheme. In this manner, the paths for the first $k-1$ body parts can possibly be updated during the planning of the $k^{th}$ body part. This form of sequential planning along with path refinement helps us treat the whole-body as a tightly coupled system.

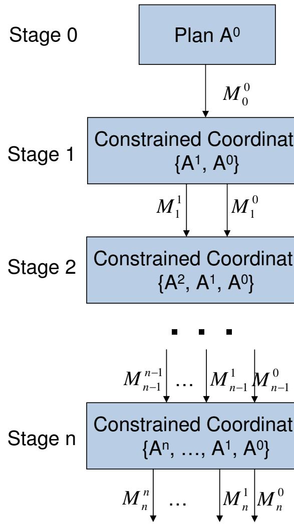



Fig. 3. *Whole-Body Motion Planning using Constrained Coordination. We first compute the path for $A^0$ while ignoring all the other parts. When planning the motion for the system $\{A^0,A^1\}$, the motion of $A^0$ is constrained on the path $M_0^0(t)$ but this path can be locally refined. We refer this step as constrained coordination (Fig. 4).*

### A. Decomposition of a Human-like Model

The simplest decomposition of a human-like robot decomposes the whole-body into different body parts $\{A^0,A^1,...,A^n\}$. In this case, it is assumed that each $A^i$ has few DOF. Fig. 1 shows a decomposition scheme, where a human model is decomposed into parts: a lower-body (including legs and pelvis), torso, head, left arm and right arm. In this decomposition, the lower body is treated as the root of the tree. It is possible to compute another decomposition where the root node ($A^0$) corresponds to the torso. Furthermore, we build a hierarchical representation based on the inter-connection between the parts. For example, each arm can be further decomposed into upper arm, lower arm, hand, etc.

We use the symbol $\mathbf{q}$ to denote the configuration of a human-like robot. $\mathbf{q}$ is composed of configurations $\mathbf{q}^i$ for each body part, i.e. $\mathbf{q} = (\mathbf{q}^0,\mathbf{q}^1,...,\mathbf{q}^n)$, where $\mathbf{q^i}$ corresponds to the configuration of $A^i$. Since we are dealing with articulated models, the configuration $\mathbf{q}^i$ for $A^i$ is determined by all of its actuated joints, including the joint through which $A^i$ is connected to its parent body part in the decomposition tree. For the lower body part $A_0$, 6 additional unactuated DOF can be added to the system to specify the position and orientation of the coordinate frame associated with the pelvis For instance, The basic motion planning problem for a human-like robot is to find a collision-free path between the starting configuration $\mathbf{q}_s = (\mathbf{q}_s^0,\mathbf{q}_s^1,...,\mathbf{q}_s^n)$ to the goal configuration $\mathbf{q}_g = (\mathbf{q}_g^0,\mathbf{q}_g^1,...,\mathbf{q}_g^n)$. In practice, the resulting motion should also satisfy with statically or dynamically stable constraints.

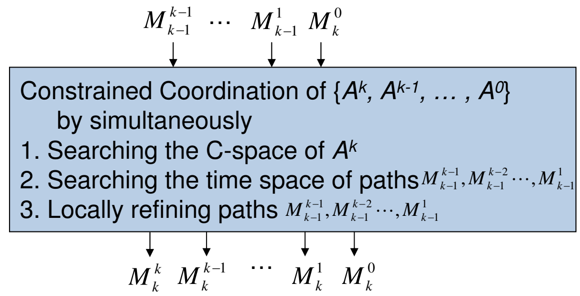



Fig. 4. *Constrained coordination algorithm: It includes a path computation stage for the new part and refinement of the paths of the other parts.*

### B. Whole-Body Motion Planning using Constrained Coordination

A human-like model is a tightly coupled system and the inter-connection between the body parts needs to be maintained during planning. One possibility is to decompose this high dimensional robot into a multi-robot planning problem by treating each part as a separate robot. There is rich literature on multi-robot motion planning and at a broad level prior approaches for multi-robot planning can be classified into centralized or decentralized methods. The centralized methods compose all the different robots into one large coupled system. The DOF of the coupled system corresponds to the sum of DOF of all the robots. Such an approach could be extremely inefficient for a human-like robot due to the high DOF configuration space. The decentralized planners compromise on the completeness by using a decoupled approach. The decentralized planner typically proceeds in two phases. In the first phase, a collision-free path is computed for each robot with respect to the obstacles and the collisions between the robots are handled in the second phase by adjusting their velocities. Since a human-like robot is a tightly coupled system, it would be hard using purely decoupled methods to maintain the inter-connection constraints between adjacent links of the robot.

We propose a hybrid coordination scheme that is based on prior work on prioritized or incremental coordination approaches [9], [28]. Our algorithm proceeds hierarchically using the decomposition of the human model and computes the path of different nodes in the tree in a breadth-first way. The path computed for a part corresponding to a node, also takes into the account the path of its parent node and other paths computed so far.

We describe the main idea behind constrained coordination by taking into account two objects, $A$ and $B$. Suppose $A$ has $m$ DOF and $B$ has $n$ DOF. By considering the two objects as a composite system, $\{A,B\}$, a centralized planner needs to search over a $m+n$ dimensional space. On the other hand, decentralized approaches plan each object independently by searching the $m$ and $n$ dimensional spaces corresponding to each robot. We improve the decentralized planning by using an incremental coordination strategy. A collision-free path $M^A(t)$ for $A$ is computed by ignoring $B$. Next, a collision-free path for the system $\{A,B\}$ is computed by coordinating

$A$ and $B$. During the coordination, a *path constraint* for $A$ is imposed so that the configuration of $A$ should lie on the path $M^A(t)$. The coordination of the system $\{A,B\}$ is the $n+1$ dimensional search space, since $A$ is constrained on a one-dimensional path with the parameter $t$ and $A^1$ has $n$ DOF. Intuitively, this approach computes a path for $B$ (i.e. $M^B(t)$), based on the original trajectory ($M^A(t)$) computed for $A$. However, it is possible that the original path computed for $A$ may not result in a feasible path for $B$ such that $\{A,B\}$ may satisfy all the collision and dynamics constraints as shown in Fig. 5. In the case of human-like motion, such a hard constraint can result in either an inefficient planner or a failure to compute a solution that satisfies all the constraints. In order to address this issue, we use a local refinement scheme that modifies the computed trajectory $M^A(t)$, as it computes a collision-free path for $B$. In Section IV, we present an implicit local path refinement algorithm based on constrained sampling and interpolations.

### *C. Planning Stable Motions*

In addition to collision-free and joint limit constraints, the motion of human-like robots is subject to statically or dynamically stable constraints. The computed postures should either be statically stable, i.e. the projection of the center of mass of the robot (CoM) lies inside the foot support polygon, or dynamically stable, i.e. the zero moment point (ZMP) lies inside the support polygon [31]. However, due to the computational complexity necessary to plan the collision-free and dynamic motion together, most previous approaches tend to use a decoupled two-stage framework [12], [20], [35]. For instance, a collision-free path can be first computed. The path then is transformed into a dynamically stable trajectory. Each of these stages is iterated until both types of constraints are satisfied (Fig. 2). Our approach can be extended to compute a statically stable motion. If any sample generated by the constrained coordination algorithm is not statically stable, we further modify the sample by using inverse kinematics (IK) so that the CoM at the new sample lies inside the approximate foot support polygon. Within the two-stage framework, our approach can improve the efficiency of the first stage on computing a collision-free and statically stable path. Such path is further processed by the second stage.

## IV. Constrained Coordination

In this section, we present our constrained coordination approach. It is primarily designed for human-like or tightly coupled robots that have high DOF. Our approach consists of two parts: a modified incremental coordination algorithm and local path refinement.

### *A. Path Computation*

Our algorithm proceeds in multiple stages, as shown in Fig. 3. We use the symbol $M^i_j(t)$ to denote the path of part $A^i$ computed after stage $j$. After stage $j$, the algorithm has computed the following paths: $M^i_j(t)$ for $A^i$, for $i=0,1,\ldots,j$. As shown in Fig. 4, during this stage, the algorithm computes

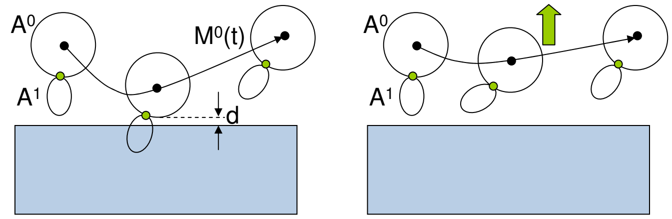



Fig. 5. *Given an articulated robot with two links $A^0$ and $A^1$, a path $M^0(t)$ for $A^0$ is first computed. However, when $A^0$ moves along $M^0(t)$, it comes very close to the obstacle (shown in blue), as the separation distance $d$ is very small. This leads to no feasible placement for $A^1$, as it collides. To resolve such cases, our constrained coordination scheme locally refines the path $M^0(t)$ by moving it upwards (shown with green arrow), while planning the motion for $A^1$. In practice, such a local refinement approach is more efficient as compared to global replanning.*

paths for $A^0$, $A^1$, $\ldots$, $A^j$ by simultaneously searching the C-space of $A^j$ and the 1 dimensional time space of the set of paths $(M^0_{j-1}(t), M^1_{j-1}(t), \ldots, M^{j-1}_{j-1}(t))$, and locally refining each of the paths $M^0_{j-1}(t), M^1_{j-1}(t), \ldots, M^{j-1}_{j-1}(t)$. Later, we show the local path refinement can be performed implicitly within a sample-based planner. The algorithm traverses the entire hierarchy of body parts, $\{A^0,\ldots,A^n\}$, sequentially in the breadth-first order of the tree. After stage $n$, the algorithm has computed a path for all the parts that satisfy the constraints.

### *B. Implicit Local Path Refinement*

A key aspect of our constrained coordination algorithm is refining the path that was computed at the previous stage. In this section, we present a local replanning algorithm that takes into account the decomposition of human-like robots and the path computation algorithm highlighted above. We observe that within an incremental coordination scheme for two objects $\{A^0, A^1\}$, the motion of $A^0$ is strictly constrained on the path computed earlier. This can lead to the difficulty of planning a motion for the overall robot, or the failure in terms of finding a solution. Fig. 5 shows such an example for an articulated robot with two links $A^0$ and $A^1$. When $A^0$ moves along the path $M^0_0(t)$, its distance $d$ to the obstacle becomes too small, which results in no feasible placement for $A^1$. This issue can arise when we are attempting to compute a collision free path in a cluttered environment or in a narrow passage. Since the robot is decomposed into many body parts, each body part is constrained by predecessors, as given by the breath first order of the tree. In this case, we refine the path for $A^0$, given as $M^0_0(t)$, and compute a new path $M^0_1(t)$.

Our algorithm uses a sample-based planner to compute a path during each stage and we design an implicit local refinement scheme that can be integrated with any sample-based approach. The two main steps of sample-based planning is generating samples in the free space and computing an interpolating motion between those samples using local planning. Instead of explicitly modifying the path computed in the previous stage, our algorithm performs *constrained sampling* and *constrained interpolation* so that the generated samples or local motions are allowed to move away from the

**Algorithm 1**: Constrained Sampling

**Input**: Body parts $A^0$ and $A^1$;
A collision-free path $M^0(t), t \in [0,1]$ for $A^0$
**Output**: A random configuration $(\mathbf{q}^0, \mathbf{q}^1)$ for $\{A^0, A^1\}$ where $\mathbf{q}^0$ subjects to the path constraint $M^0$
**begin**
$\mathbf{q}^1$ = Random configuration of $A^1$
// Sampling the path $M^0$
$t_{rand} = Rand(0,1)$
$\mathbf{q}^0 = M^0(t_{rand})$
// Perturbation
$\mathbf{r}$ = Shortest vector from any obstacle to $A^0$
$\lambda$ = A random scale factor (See Section IV.B)
$\Delta\mathbf{r} = \lambda\mathbf{r}$
$\Delta\mathbf{q}^0$ = InverseKinematics($A^0$, $\mathbf{q}_0$, $\Delta\mathbf{r}$)
$\tilde{\mathbf{q}}^0 = \mathbf{q}^0 + \Delta\mathbf{q}^0$
**return** $(\tilde{\mathbf{q}}^0, \mathbf{q}^1)$
**end**

constraining path up to a threshold. In this way, we achieve the path refinement implicitly. In the following, we present the algorithm for a composite system with two robots, which can be generalized to a system with $n$ robots.

*1) Constrained Sampling:* Our algorithm (Alg. 1) generates a configuration for the system $\{A^0, A^1\}$ subject to the path constraint. A configuration $\mathbf{q}^1$ for $A^1$ is computed by randomly sampling its configuration space. A configuration of $A^0$ is computed by randomly generating a value $t_{rand}$ on the path $M^0(t)$, which lies in the coordination space $[0,1]$. If the composite configuration $(M^0(t_{rand}), \mathbf{q}^1)$ is collision free for the system $\{A^0, A^1\}$, it can be used by a sample-based planner. Otherwise, we perturb the configuration as part of the refinement step.

We determine the closest points between $A^0$ at the configuration $M^0(t_{rand})$ and the obstacles. Let us denote the closest point on $A^0$ using $\mathbf{p}$ and let $\mathbf{r}$ be the vector from the closest point of the obstacles to $\mathbf{p}$. The basic idea for perturbing the configuration $M^0(t_{rand})$ for $A^0$ is to increase the clearance between $A^0$ and the obstacles so that we can avoid the situations shown in Fig. 6. In order to perform such a perturbation, we randomly choose a scale factor $\lambda$. The desired displacement for the point $\mathbf{p}$ in the workspace after the perturbation then is $\Delta\mathbf{r} = \lambda\mathbf{r}$. $\lambda$ is chosen larger than $-1$, which can guarantee that the point $\mathbf{p}$ does not collide with obstacles when $A^0$ moves. Furthermore, a Gaussian distribution function is used when randomly choosing $\lambda$ so that the probability of choosing a value near to 0 is higher. Therefore, the constrained sampling algorithm has higher probability of generating samples near the constraint path. Finally, we compute the amount of perturbation $\Delta\mathbf{q}^0$ for $A^0$ by solving the inverse kinematic problem, $\Delta\mathbf{r} = \mathbf{J}^0_\mathbf{p}\Delta\mathbf{q}^0$, where $\mathbf{J}^0_\mathbf{p}$ is the Jacobian for the point $\mathbf{p}$ on $A^0$.

*2) Constrained Interpolation:* We address the issue of motion interpolation during our path refinement algorithm. Given two configurations of the system $\{A^0, A^1\}$, our goal is to interpolate a motion between them that satisfies the path constraint. The interpolation between the two configurations of the body part $A^1$ can be computed by a linear or other

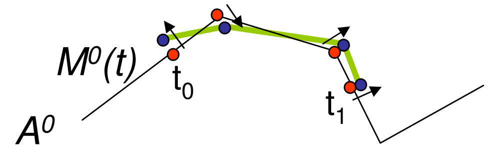


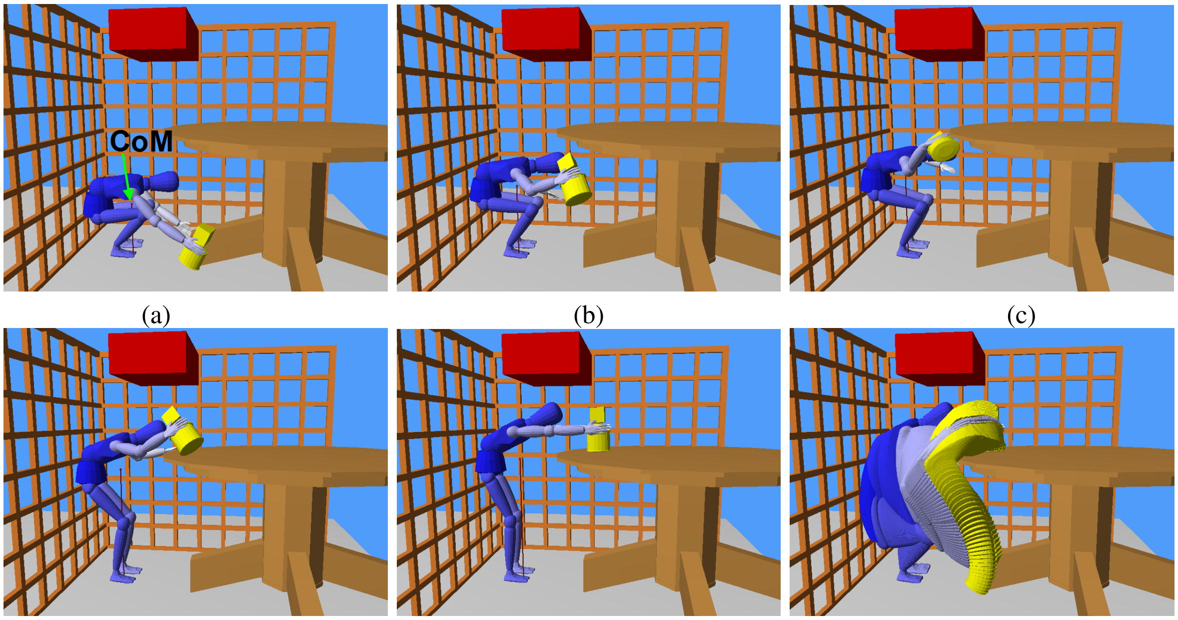

Fig. 6. *Our constrained coordination approach does not strictly constrain the motion of $A^0$ on the path $M^0(t)$. Rather, $A^0$ is allowed to move away from the path locally based on refinement. The extent of perturbation is determined by a Gaussian distribution function. Within a sample-based planner, the local path refinement is implicitly performed by using our constrained sampling and constrained interpolation schemes.*

interpolation algorithm. Differently, when interpolating the two configurations of $A^0$, the resulting motion of $A^0$ should be constrained on the path $M^0(t)$ computed earlier. Let us denote $t_0$ and $t_1$ as the parameters of the two configurations of $A^0$ on the path $M^0(t)$. The interpolation for $A_0$ is constrained on the path $M^0(t)$ and passes all the nodes along the path between $t_0$ and $t_1$ as shown in Fig. 6. Together with the interpolating motion for $A_1$, we finally obtain a constrained interpolating motion for the entire system $\{A^0, A^1\}$. If the new interpolation for the system is not collision free, we locally perturb these nodes by changing the configurations for $A_0$ using the perturbation described above. The resulting interpolating motion is used by a sample-based planner.

## C. Statically Stable Motion

Our constrained coordination algorithm can be extended to generate a statically stable motion for a robot. In the coordination algorithm, we modify the last stage for coordinating between $A_n$ and $\{A_0, A_1, \ldots, A_{n-1}\}$. During this stage, we also check whether the configuration $\mathbf{q}$ generated from constrained sampling is statically stable, i.e. the projection of the center mass (CoM) point of the robot at $\mathbf{q}$ lies inside the support polygon defined by the robot's support feet (foot for single foot support case). If the configuration $\mathbf{q}$ is not statically stable, we perturb it to generate a statically stable configuration $\mathbf{q}'$ and ensure that the foot placement is not changed. The perturbation step is reduced to an inverse kinematic problem. The projection of CoM point is treated as one end-effector in the IK problem. The Jacobian of this end-effector can be easily derived according to the kinematics of the robot and the mass of each body part. In the IK problem formulation, this end-effector needs to be moved toward the center of the support polygon until it is inside the polygon. In order to maintain the foot contact constraint, we choose three contact points from each contact foot as additional end-effectors. Their positions are not changed. To solve the IK problem, we use a damped least squares method [3].

The modified constrained sampling allows us to generate statically stable samples for sample-based planners. We also need to check whether the interpolating motion between samples is statically stable. One simple way is to discretely sample along the interpolating motion and check each sample individually. If any sample is not statically stable, we can perturb it by using our IK-based CoM perturbation technique.




(a) (b) (c)

(d) (e) (f)

Fig. 7. *The crouching robot picks the object from the ground and puts it on the table (a-e). When performing this task, the robot needs to avoid the collision with the environment and maintain its balance. Our algorithm can efficiently compute a valid motion for the robot within* 10.1*s. The entire motion is shown in (f). We highlight the center of mass (CoM) of the robot at each configuration. The projection of CoM onto the ground shows that the robot maintains the statically stable constraint along the motion we have computed.*

Fig. 8. *The robot moves toward one chair and sits down. To avoid the collision with the overhead light, the robot needs to bend itself. This scenario has narrow passages and tight spaces, and therefore, the planner takes more time.*

## V. Implementation and Results

In this section, we describe our implementation and the performance of our algorithm in many complex scenarios. We use a human-like robot with 40 DOF as shown in Fig. 1. The robot model is mobile and able to bend the torso or head and sit. Six of the 40 DOF are unactuated and used to specify the position and orientation of the virtual base. The robot is modeled by $22K$ triangles and it is decomposed into five body parts $\{A^0, A^1, \ldots, A^4\}$ in our benchmarks. The number of DOF for each body part is specified in Fig. 1.

The underlying planner uses a sample-based path computation algorithm - bidirectional RRT [22]. We also augment the sampling and motion interpolation components to perform local path refinement. When planning the motion for the first $k$ parts of the robots, we ignore the rest of the body parts by temporarily deactivating those parts from motion. Moreover, we use PQP library for collision detection and closest distance queries with the obstacles and also among various parts of the robot. We use a damped least squares method for computing IK [3]. Our current implementation is not optimized and it is possible to further improve the running time.

Figs. 7,8,9,10 show four complex scenarios that are used to analyze the performance of our algorithm. The resulting algorithm computes motion strategies corresponding to bending, standing up, and grabbing objects in complex scenarios. In Fig. 7, the robot is crouching. In order to pick the object from the ground and put it on the table, the robot needs to first stand up and then bend its torso. Our algorithm can efficiently compute a collision-free motion to achieve this task within 10.1s on a Pentium IV PC. The second scenario shows the motion of the human-like robot in a dining room (see Fig. 8). In this case, the robot walks from its initial position towards the dining table and eventually sits down. In Fig. 9, a whole-body motion for the robot is computed by our planner. The robot is able to pass through a tight space or a narrow passage between the two bookshelves. When the robot passes through the narrow passage, it needs to coordinate its arm motion as well as its lower body motion to avoid collisions with the obstacles. The total computational time to compute a collision-free path for this benchmark is 18.3s.

In Fig. 10, we show a scenario arising in CAD application. The human-like robot's right hand is grabbing a tool. The human-like robot needs to move his body inside the car to fix some parts using the tool. The CAD model of the car has $244k$ triangles and the algorithm needs to check for collisions with the car seat, roof and other parts. Our algorithm can efficiently compute a collision-free motion for this benchmark in 25.1s.

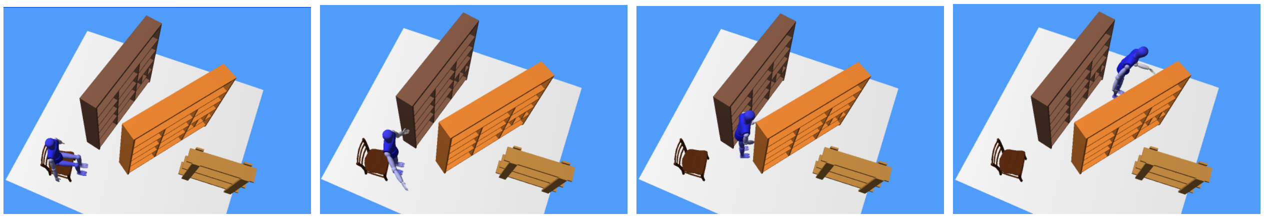


Fig. 9. *The robot passes through a narrow passage between two bookshelves.*

| Stage | Bookshelves | | Dinning Room | | Car | | Crouching | |
|---|---|---|---|---|---|---|---|---|
| | Time (s) | Nodes | Time (s) | Nodes | Time (s) | Nodes | Time (s) | Nodes |
| $A^0$ | 4.719 | 269 | 24.328 | 559 | 0.407 | 51 | 0.100 | 102 |
| $A^0$, $A^1$ | 2.180 | 115 | 5.719 | 134 | 0.563 | 100 | 1.063 | 104 |
| $A^0$, $A^1$, $A^2$ | 2.165 | 126 | 6.000 | 132 | 1.719 | 237 | 1.234 | 105 |
| $A^0$, $A^1$, $A^2$, $A^3$ | 5.201 | 89 | 6.796 | 74 | 16.891 | 1,436 | 4.266 | 183 |
| $A^0$, $A^1$, $A^2$, $A^3$, $A^4$ | 3.504 | 80 | 14.641 | 168 | 5.453 | 257 | 3.375 | 109 |
| Overall Planning | 18.328(s) | | 56.809(s) | | 25.078(s) | | 10.117(s) | |

TABLE I

*Performance of our approach on various benchmarks. We show the timing and the nodes in the resulting RRT at each stage of our constrained coordination. We also highlight the total timing for each benchmark. Our approach computes a collision-free path for the human-like robot with up to tens of seconds on various scenarios.*

| | Bookshelves | Dinning Room | Car | Crouching |
|---|---|---|---|---|
| Decomposition as Fig. 1 (s) | 18.3 | 56.8 | 25.0 | 10.1 |
| Decomposition of lower and upper bodies (s) | 84.3 | 63.8 | 69.6 | 19.7 |
| Centralized approach (s) | 191.6 | 73.0 | 113.3 | 73.4 |

TABLE II

*Comparison of the performance between our approaches based on different decomposition schemes and the centralized approach.*

In table I, we show the timing and nodes corresponding to each stage of the constrained coordination algorithm. In these examples, the locomotion such as walking, sitting and standing up are currently generated using kinematic pattern generators (e.g. a walking cycle generator).

We compared the performance of our approach based on the decomposition in Fig. 1, our approach based on the lower-body and upper body decomposition, and the centralized planner applied to the entire robot. Table II shows that our approach can achieve up to 10 times speedup in the performance over the centralized approach. Our approach often achieves more speedups in more cluttered environments.

**Limitations.** Our approach has some limitations. The underlying planner is not complete and its performance can vary with the scenario and the start or goal configurations. The performance depends considerably on the quality of specific paths computed for the previous stages. In the subsequent stages, we only use local refinement techniques to perform local modifications to the path. Secondly, due to randomized sampling, the motion computed by our planner can be unnatural, especially when the robot is in open environment. Recently, by combining the motion computed by our planner with motion capture data, we can synthesize more natural motion [25].

## VI. Conclusions and Future Work

In this paper, we have presented an algorithm to compute whole-body motion for human-like robots. Our approach can handle high-DOF robots and uses decomposition strategies to reduce the problem to a sequence of low-dimensional problems. We use a constrained coordination approach that solves each sub-problem incrementally, and performs local refinement to satisfy collision-free and statically stable constraints on CoM. We have demonstrated the performance on a 40-DOF robot in complex scenarios and generated collision-free motion paths corresponding to walking, sitting, bending in complex scenes with tight spaces and narrow passages.

There are many avenues for future work. It is interesting to extend our approach for the situations when the kinematic model of the robot forms single or multiple closed loops. For such situations, inverse kinematic methods can be used to obtain closed loops. We would also like to compute dynamically stable motions. Finally, we are interested in experimenting on more complex scenarios [24] with more DOF and difficult narrow passages that arise in virtual prototyping and applying our approach to digital human modeling and ergonomic analysis.

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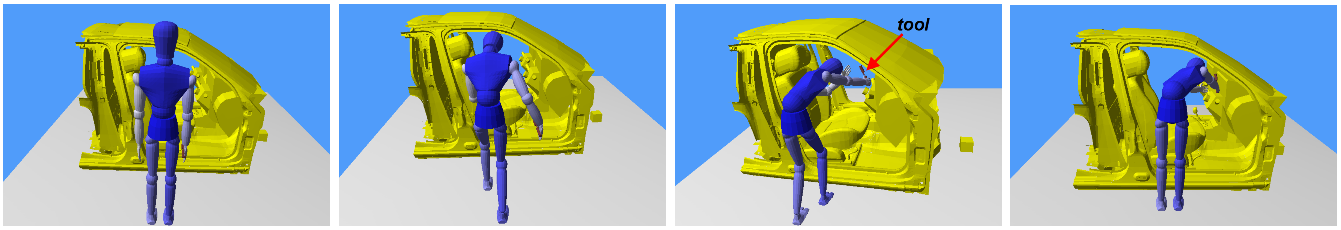


Fig. 10. *The robot's right hand is grabbing a tool. The robot needs to move its upper-body inside a car to fix some parts with the tool. Our algorithm can efficiently compute a collision-free motion for the robot in* 25.1*s.*

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