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WHOLE-BODY DYNAMIC BEHAVIOR AND CONTROL OF HUMAN-LIKE ROBOTS

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With the increasing complexity of humanoid mechanisms and their desired capabilities, there is a pressing need for a generalized framework where a desired whole-body motion behavior can be easily specified and controlled. Our hypothesis is that human motion results from simultaneously performing multiple objectives in a hierarchical manner, and we have analogously developed a prioritized, multiple-task control framework. The operational space formulation[10] provides dynamic models at the task level and structures for decoupled task and posture control.[13] This formulation allows for posture objectives to be controlled without dynamically interfering with the operational task. Achieving higher performance of posture objectives requires precise models of their dynamic behaviors. In this paper we complete the picture of task descriptions and whole-body dynamic control by establishing models of the dynamic behavior of secondary task objectives within the posture space. Using these models, we present a whole-body control framework that decouples the interaction between the task and postural objectives and compensates for the dynamics in their respective spaces.

Keywords: Whole-body control; task dynamics; posture dynamics; decoupled posture control; operational space formulation.

1. Introduction

The successful introduction of robotics into human environments will rely on the development of competent and practical systems that are dependable, safe, and easy to use. To work, cooperate, assist, and interact with humans, the new generation of robots must have mechanical structures that accommodate the interaction with the human and adequately fit in his unstructured and sizable environment. Human-compatible robotic structures must integrate mobility (legged or wheeled) and manipulation (preferably bi-manual), while providing the needed access to perception and monitoring (head vision).[1,5,13,17,20,21] These requirements imply robots with branching structures — tree-like topology involving much larger numbers of

Fig. 1. **Redundancy:** These superimposed images display the redundancy property for a given task. The robot can take multiple configurations while maintaining fixed locations for its hands.

degrees of freedom than those usually found in conventional industrial robots. The substantial increase in the dimensions of the corresponding configuration spaces of these robots renders the set of fundamental problems associated with their modeling, programming, planning, and control much more challenging.

Among the major challenges is whole-robot motion modeling, motion coordination, and dynamic control. For robots with human-like structures, tasks are not limited to the specification of the position and orientation of a single effector. For these robots, task descriptions may involve combinations of coordinates associated with the arms, the legs, the head-camera, and/or the torso among others. The remaining freedom of motion may be assigned to various criteria related to the robot posture and its internal and environmental constraints.

There is a large body of work devoted to the study of motion coordination in the context of kinematic redundancy.[2,7] In recent years, algorithms developed for redundant manipulators have been extended to mobile manipulation robots.[6] Typical approaches to motion coordination of redundant systems rely on the use of pseudo or generalized inverses to solve an under-constrained or degenerate system of linear equations, while optimizing some given criterion.[3,4] These algorithms are generally driven by kinematic considerations and the dynamic interaction between the end effector and the robot's self motions is ignored.

Our effort in this area has resulted in a *task-oriented* framework for whole-robot dynamic coordination and control.[14] The dynamic coordination strategy we have developed is based on two models concerned with task dynamics[10] and robot posture behavior. The *task dynamic behavior* model is obtained by a projection of the robot dynamics into the space associated with the task, while *the posture behavior* is obtained by the complement of this projection. We later introduced the concept of dynamically consistent posture control,[12] which guarantees posture behaviors to be performed without projecting any acceleration onto the task (see Fig. 3). However, this initial approach did not consider the dynamics of the posture itself. As a result, dynamic effects from the primary task and improper control gains results in limited performance for secondary behaviors.

Other researchers have considered the dynamic interaction between the task and posture spaces and have proposed an extension to the operational space formulation.[18] However, this approach uses semi-coordinate representations of the posture space and does not consider the manner in which subtask objectives are achieved in the posture space. In contrast, we provide models for the dynamics of secondary tasks within the restricted posture space. These proposed subtask dynamic behavior models allow for the compensation of the dynamics in the task-dependent posture space to improve the control of postural objectives. The posture goal may not be completely achievable if it conflicts with the primary task, but the new framework allows for full control of posture subtasks *within the restricted space* defined by the task. Including these subtask dynamic behavior models within the operational space framework, we introduce a framework for multiple task, whole-body description and control.

The strength of this new approach lies in its performance, generality, and overall simplicity. While supervised learning,[8] rapid motion planning[9,15] and explicit specification of trajectories[16] have been successfully implemented for various applications, they all share the difficulty of offline trajectory generation which restricts the scope of their application. Should the desired task be modified to a related but different objective, further offline processing is required and the complete design procedure may need repeating (e.g. provide a new teaching demonstration, or complete reconstruction of the desired trajectory). Furthermore, it is also unclear how to best modify these approaches to achieve multiple tasks simultaneously. Addressing these issues, the new framework is indeed not limited to only a single subtask, but can be recursively extended to control multiple desired behaviors. We can therefore provide a prioritized list of desired behaviors for the human-like robot, and the controller performs all tasks to the extent that they do not conflict with higher priority ones.

2. Human Motivated Control

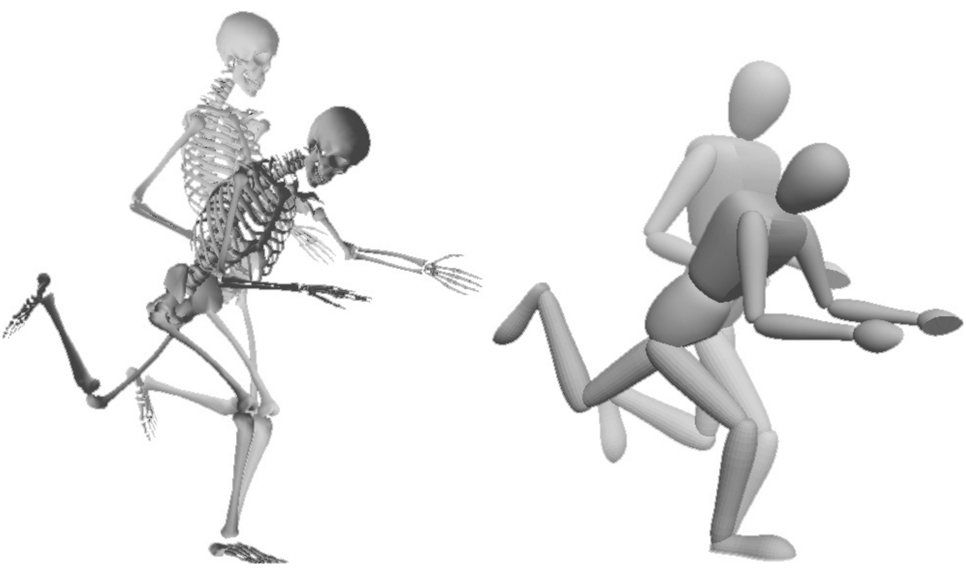
With the introduction of human-like structures into robotic mechanisms, control of these robots faces new challenges. In contrast with the rigid, artificial motions associated with industrial manipulators, humanoid robots should move in a manner indistinguishable from humans. This human/humanoid compatibility is required to facilitate robot interaction and promote humanoid acceptance within the everyday world.

However, the criteria for natural motion are not easily described. People consider many factors while performing everyday tasks — physical strain, the presence of obstacles in their environment, and more abstractly, cultural and social norms. The priorities of these factors differ among tasks, but each behavior is fully performed subject to the limitations imposed by more critical behaviors. Thus, humanoids must similarly handle multiple tasks in a prioritized manner.

The concept of utilizing human motion as a basis for robotic control is not new. Human hand motion is approximately linear in Cartesian space, which motivated the derivation of the operational space framework. Extensions to the operational space framework demonstrated that kinematic redundancy can be utilized to control other tasks, so we return to human motion to identify these additional behaviors.

Our model for human motion is that each behavior can be modeled independently as energy potentials, and that natural motion results by attempting to minimize these potentials. Currently we are identifying posture energies by analyzing constrained human motion through motion capture technologies. Once identified, these energies can be directly applied to robotic control (see Fig. 2). By identifying more human-inspired energy functions, we intend to form a basis describing most human motion. Humanoid control will therefore be reduced to describing the weights and priorities of these basis behaviors.

Independent of the process of identifying postural energies, a humanoid robot will require a control structure to perform all desired behaviors in a prioritized manner. By constructing dynamic behavior models of secondary tasks within the posture space, we provide one possible solution. This work presents the first but



(a) (b)

Fig. 2. **Human Posture Potentials:** By use of immersive video motion capture techniques, we are (a) identifying energy functions describing human motion and (b) mapping them to humanoid robots for control.

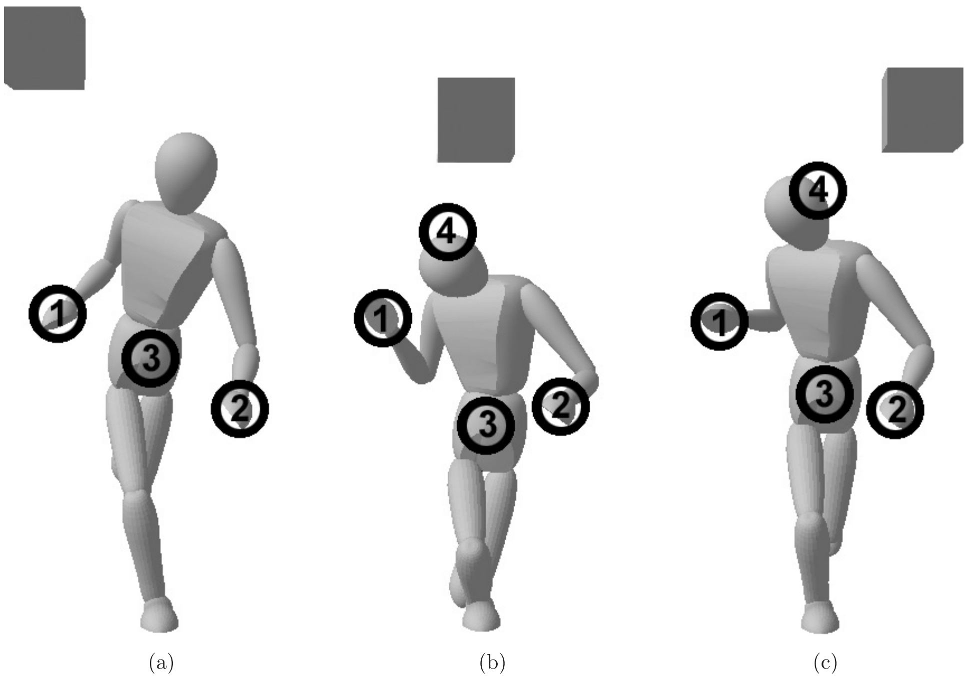


Fig. 3. **Multiple Task Control:** This sequence of snapshots demonstrates the humanoid robot performing multiple tasks simultaneously. In snapshot (a), the robot places its hands in fixed locations (Tasks **1** and **2**) while controlling the global center of mass to maintain balance (Task **3**). Snapshots (b) and (c) exhibit the robot performing these tasks while maintaining a threshold distance to nearby obstacles (Task **4**).

vital step in the process of mapping human dynamics and motion behaviors onto human-like structures.

3. Whole-Robot Control: Motion Behaviors

For a given desired whole-body task of a human-like robot, we must specify the motion behaviors to be controlled during the execution of the motion. Hand location, balance, effort minimization, and obstacle and joint limit avoidance are common choices, but the exhaustive list depends upon the motion to be performed. Considering each behavior as an independent task, the number of degrees of freedom describing each task is typically less than the number of joints in the robot. For these situations, there are multiple ways of performing the task. We label this redundancy in solutions as the posture space of the task, containing all possible motions that do not affect task performance. As such, other tasks may be controlled by selectively choosing the path within the posture space.

In this section we consider a situation with two behaviors: one being the primary task, the other a subtask to be controlled in the posture space. We first review the dynamic model of the primary task and the task/posture decomposition. We then introduce a new dynamic model describing the motion of the subtask within the posture space. Combining these two models, we establish a new control structure that compensates for the dynamics in both spaces, significantly improving performance and responsiveness for multiple tasks.

3.1. *Task and posture decomposition*

The task of a human-like robot generally involves descriptions of various parts of the multi-body mechanism, each represented by an operational point $x_t(i)$. The full task is represented as the $m \times 1$ vector, x_t, formed by vertically concatenating the coordinates of the operational points. The Jacobian associated with this task is denoted as $J_t(q)$.

The derivation of the operational space formulation begins with the joint space dynamics of the robot

$$A(q)\ddot{q} + b(q,\dot{q}) + g(q) = \Gamma, \tag{1}$$

where q is the vector of n joint coordinates, $A(q)$ is the $n \times n$ kinetic energy matrix, $b(q,\dot{q})$ is the vector of centrifugal and Coriolis joint forces, $g(q)$ is the vector of gravity, and Γ is the vector of generalized joint forces. To simplify notation, dependency upon the joint angles is no longer denoted.

The dynamically consistent generalized inverse[10] of J_t is

$$\bar{J}_t(q) = A^{-1}J_t^T\left[J_t A^{-1} J_t^T\right]^{-1} \tag{2}$$

and the task dynamic behavior is obtained by projecting the robot dynamics into the space associated with the task:

$$\bar{J}_t^T\left[A\ddot{q} + b + g = \Gamma\right] \Rightarrow \Lambda_t(x_t)\ddot{x}_t + \mu_t(x_t,\dot{x}_t) + p_t(x_t) = F_t. \tag{3}$$

In this space, $\Lambda_t(x_t)$ is the $m \times m$ kinetic energy matrix associated with the task, $\mu_t(x_t,\dot{x}_t)$, $p_t(x_t)$, and F_t are respectively the centrifugal and Coriolis force vector, gravity force vector, and generalized force vector acting in operational space.

This generalized torque/force relationship[11,12] allows for the decomposition of the total torque into two dynamically decoupled torque vectors: the torque corresponding to the commanded task behavior and the torque that only affects posture behaviors in the null space:

$$\Gamma = \Gamma_{\text{task}} + \Gamma_{\text{posture}}. \tag{4}$$

The operational space formulation determines the torque component for the task to compensate for the dynamics in the task space. For a task behavior with decoupled dynamics and unit inertial properties $\ddot{x}_t = F_t^*$, this torque is determined by the force transformation

$$\Gamma_{\text{task}} = J_t^T F_t, \tag{5}$$

where the operational space force is given by

$$F_t = \hat{\Lambda}_t F_t^* + \hat{\mu}_t + \hat{p}_t, \tag{6}$$

where $\hat{.}$ denotes the estimates of the various components of the dynamic model.

The second vector, Γ_{posture}, in the decomposition of Eq. (4) provides the posture control torques that do not interfere with the task. The general form of Γ_{posture} is

$$\Gamma_{\text{posture}} = N_t^T \Gamma_p, \tag{7}$$

where Γ_p is the torque vector designed to control the desired posture. This vector is projected into the posture space by

$$N_t^T(q) = \left[I - J_t^T \bar{J}_t^T \right] \tag{8}$$

to achieve dynamic consistency with the task. The torque decomposition thus takes the form

$$\Gamma = \Gamma_{\text{task}} + \Gamma_{\text{posture}} = J_t^T F_t + N_t^T \Gamma_p. \tag{9}$$

With this control structure, additional subtasks for the posture could possibly be addressed by selecting Γ_p in the same manner as Γ_{task}. However, this approach fails to address the significant effect of the null space projection matrix N_t^T. In the next subsection, we consider the effects of this projection and establish the dynamics of tasks in the posture space.

3.2. *Posture dynamic behavior and control*

First we establish the description of postures. Postures will be uniquely determined by minimal sets of independent posture coordinates. Similar to an operational task, we introduce $\dot{x}_p = J_p(q)\,\dot{q}$ where J_p is the subtask Jacobian matrix associated with the posture. To control the posture behavior, we would select command torques as if it were the task in (5):

$$\Gamma_{\text{p}} = J_p^T F_p. \tag{10}$$

However, using the task-dependent torque decomposition from (9), we obtain

$$\Gamma = J_t^T F_t + N_t^T \big(J_p^T F_p \big). \tag{11}$$

In this form, the posture torque can be rewritten as

$$\Gamma_{\text{posture}} = (J_p N_t)^T F_p, \tag{12}$$

revealing a Jacobian that combines the operators J_p and N_t. The range of this Jacobian $J_{p|t} = J_p N_t$ is the instantaneous space of posture motion that is consistent with the task. $J_{p|t}$ will be called the *task-consistent posture Jacobian.*

We consider the situation where the desired task and posture behaviors are not conflicting. This occurs when $J_{p|t}$ has full rank, so the dimension of the range of $J_{p|t}$ is equal to the degrees of freedom for the posture behavior. Following the methodology of the operational space formulation, the inertial properties associated with the subtask in the posture space are described by

$$\Lambda_{p|t} = [J_{p|t} A^{-1} J_{p|t}^T]^{-1}, \tag{13}$$

The dynamically consistent generalized inverse associated with $J_{p|t}$ is given by

$$\bar{J}_{p|t}(q) = A^{-1} J_{p|t}^T \Lambda_{p|t}, \tag{14}$$

Observing that $\bar{J}_{p|t}^T \Gamma_{\text{task}} = 0$, and $F_{p|t} = \bar{J}_{p|t}^T \Gamma_{\text{posture}}$, we obtain the more elaborate representation of Eq. (11)

$$\Gamma = J_t^T F_t + J_{p|t}^T F_{p|t}, \tag{15}$$

exposing the relationships $\Gamma_{\text{task}} = J_t^T F_t$ and $\Gamma_{\text{posture}} = J_{p|t}^T F_{p|t}$.

We can now obtain the full description of the subtask dynamic behavior from the projection,

$$\bar{J}_{p|t}^T [A\ddot{q} + b + g = \Gamma_{\text{task}} + \Gamma_{\text{posture}}] \Rightarrow \Lambda_{p|t} \ddot{x}_{p|t} + \mu_{p|t} + p_{p|t} = F_{p|t}, \tag{16}$$

where $\mu_{p|t}$ represents the Coriolis and centrifugal forces and $p_{p|t}$ is the gravity effect. Therefore to achieve a decoupled unit mass behavior $\ddot{x}_{p|t} = F_{p|t}^*$ in the controllable posture space, we implement

$$F_{p|t} = \hat{\Lambda}_{p|t} F_{p|t}^\star + \hat{\mu}_{p|t} + \hat{p}_{p|t}. \tag{17}$$

However, our goal is to achieve the decoupling and control of the full posture behavior $\ddot{x}_p = F_p^*$. We must therefore compensate for an acceleration $\ddot{x}_{\overline{p|t}}$ induced by Γ_{task} in the posture space. This acceleration complements the controllable part of the posture acceleration, $\ddot{x}_{p|t}$, producing

$$\ddot{x}_p = \ddot{x}_{p|t} + \ddot{x}_{\overline{p|t}}. \tag{18}$$

Thus to obtain the desired behavior at the full posture level x_p, we choose $F_{p|t}^\star$ by

$$\ddot{x}_{p|t} = F_{p|t}^\star = F_p^\star - \ddot{x}_{\overline{p|t}}. \tag{19}$$

We now return to the situation where the task and posture behaviors are in conflict. Let l denote the degrees of freedom for the posture behavior and k be the rank of $J_{p|t}$. Thus $k < l$, and there exist only k-directions of null-space controllable motions in the posture space. In the process of deriving the operational space formulation we obtain the relationship

$$\ddot{x}_{p|t} - \dot{J}_{p|t}\dot{q} + J_{p|t}A^{-1}(b+g) = (J_{p|t}A^{-1}J_{p|t})F_{p|t}. \tag{20}$$

The matrix $J_{p|t}A^{-1}J_{p|t}^T$ was previously inverted to obtain the posture space inertia matrix, but in the case of task/posture conflict it is singular with rank k. Nonetheless, $J_{p|t}A^{-1}J_{p|t}^T$ is positive semi-definite and has the eigenvalue decomposition

$$J_{p|t}A^{-1}J_{p|t}^T = [U_r \, U_n] \begin{bmatrix} \Sigma & \\ & \mathbf{0}_{(l-k)\times(l-k)} \end{bmatrix} \begin{bmatrix} U_r^T \\ U_n^T \end{bmatrix}, \tag{21}$$

where Σ is a $k \times k$ diagonal matrix of the non-zero eigenvalues, U_r is a $l \times k$ matrix with columns of the corresponding eigenvectors, and U_n is $l \times (l-k)$ matrix whose columns span the null space. We therefore observe the force $F_{p|t}$ can only induce accelerations along the eigenvectors, revealing they are precisely the null-space controllable directions of the posture.

To fully expose the dynamic behavior of the posture, we continue with projecting the dynamics into the k-dimensional subspace of the eigenvectors:

$$U_r^T[\ddot{x}_{p|t} - \dot{J}_{p|t}\dot{q} + J_{p|t}A^{-1}(b+g)] = \Sigma U_r^T F_{p|t}. \tag{22}$$

Hence the $k \times 1$ vector $\underline{\ddot{x}}_{p|t} = U_r^T \ddot{x}_{p|t}$ is an instantaneous set of minimal independent accelerations within the posture space, and inverting Σ in (22) and reintroducing the nonlinear effects provides the dynamic behavior model

$$\underline{\Lambda}_{p|t}\underline{\ddot{x}}_{p|t} + \underline{\mu}_{p|t} + \underline{p}_{p|t} = \underline{F}_{p|t}, \tag{23}$$

where $\underline{\Lambda}_{p|t} = \Sigma^{-1}$ is the inertia matrix, $\underline{F}_{p|t} = U_r^T F_{p|t}$ is the projected force, and $\underline{\mu}_{p|t}$ and $\underline{p}_{p|t}$ are the nonlinear coupling and gravity effect.

We return to the issue of control of the posture. The posture behavior (19) can no longer be obtained, but along the controllable directions we can seek the decoupled unit mass system behavior

$$\underline{\ddot{x}}_{p|t} = \underline{F}^*_{p|t} = U_r^T F^\star_{p|t} \tag{24}$$

by selecting a control reference

$$\underline{F}_{p|t} = \hat{\underline{\Lambda}}_{p|t}\underline{F}^*_{p|t} + \hat{\underline{\mu}}_{p|t} + \hat{\underline{p}}_{p|t}. \tag{25}$$

However, this force must be lifted back into the $x_{p|t}$ space by U_r:

$$\begin{aligned} F_{p|t} = U_r\underline{F}_{p|t} &= U_r\hat{\underline{\Lambda}}_{p|t}\underline{F}^*_{p|t} + U_r\left(\hat{\underline{\mu}}_{p|t} + \hat{\underline{p}}_{p|t}\right) \\ &= (\widehat{U_r\Sigma^{-1}U_r^T})F^*_{p|t} + \hat{\mu}_{p|t} + \hat{p}_{p|t}. \end{aligned} \tag{26}$$

We therefore observe an analogous control structure to (17) but with the eigenvalue decomposition of $J_{p|t}A^{-1}J_{p|t}^T$ to identify the non-conflicting directions of motion in the posture space.

This described posture space framework ties in with the task space framework, thus forming the basis of a new whole body behavior and control system for humanoid structures. We are now in a position to define specific postures and analyze their combined performance with predefined tasks.

4. Simulation and Validation

We have implemented and verified the proposed control framework in our simulation and control environment (SAI). SAI is a unique virtual environment that integrates multi-body dynamics, multi-robot control, multi-contact multi-body resolution and haptic interaction for robot teleoperation.

For real-time simulation, the multi-body dynamics and multi-contact resolution require efficient algorithms. We have developed a dynamics engine that resolves the forward and inverse dynamics of an n DOF branching multi-body system in linear time, $O(n)$. Moreover, p collisions can be resolved with a complexity of $O(np + p^3)$ using the operational space resolution model.[19] Finally, the controller has a modular design so that whole-body robot behaviors are specified as a combination of multiple motion tasks. Figure 4 illustrates a virtual real-time simulation of SAI where a humanoid is falling under the effects of the gravity and colliding with the floor at multiple contact points.

To validate our proposed controller, we have developed humanoid robotic models that can be simulated and controlled in SAI. The desired robot behaviors are described as combinations of self-contained motion tasks. For each task there is an associated cost function that can be considered as an energy potential. The controller is designed to dynamically minimize these potentials in their corresponding motion spaces.

To validate our controller, we perform two experiments. First we conduct an experiment where a secondary behavior is controllable in the posture space of the task. We then consider a secondary behavior involving the motion of all joints and therefore must conflict with the primary task. For comparison, we use two different

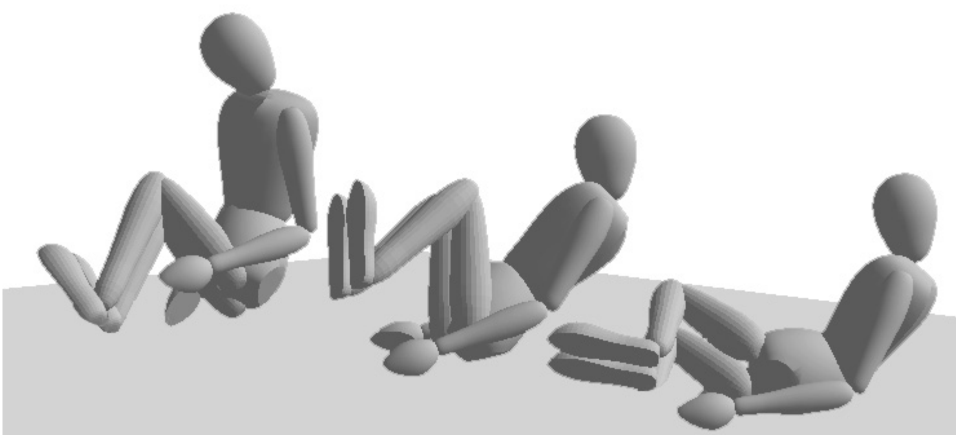


Fig. 4. **Robot Simulation:** This SAI simulation shows a robot falling due to gravity. Efficient multi-body dynamics and multi-contact algorithms resolve the simulation in real-time.

controllers for each experiment: the dynamically consistent controller discussed in this paper

$$\Gamma_{\text{posture}} = J_{p|t}^T [\hat{\Lambda}_{p|t} F_{p|t}^{\star} + \hat{\mu}_{p|t} + \hat{p}_{p|t}], \tag{27}$$

and a non-dynamically consistent controller

$$\Gamma_{\text{posture}} = J_{p|t}^T [\hat{\Lambda}_p F_p^{\star} + \hat{\mu}_p + \hat{p}_p]. \tag{28}$$

In the first experiment, the task is to maintain a fixed position of the left hand while the secondary behavior is to oscillate the left elbow. Due to the considerable kinematic redundancy for the task, the secondary behavior is fully controllable in its posture space. Figures 5 and 6 illustrate the resulting motion using the two controllers. While the non-dynamically consistent controller produces little movement at the left elbow, the dynamically consistent controller tracks the desired motion by correctly compensating for the dynamics within the posture space.

For the second experiment, the task of controlling the left hand position is unchanged. The secondary behavior is to minimize the mean square error between the joint angles and a desired joint configuration. The goal configuration is chosen to be incompatible with the task, so the secondary behavior is not completely achievable within the posture space. As observed in Fig. 7, starting from initial configuration (a), the non-dynamically consistent controller actually increases the mean square error describing the secondary behavior. In contrast, Fig. 8 demonstrates that the dynamically consistent controller locally minimizes the posture mean square error.

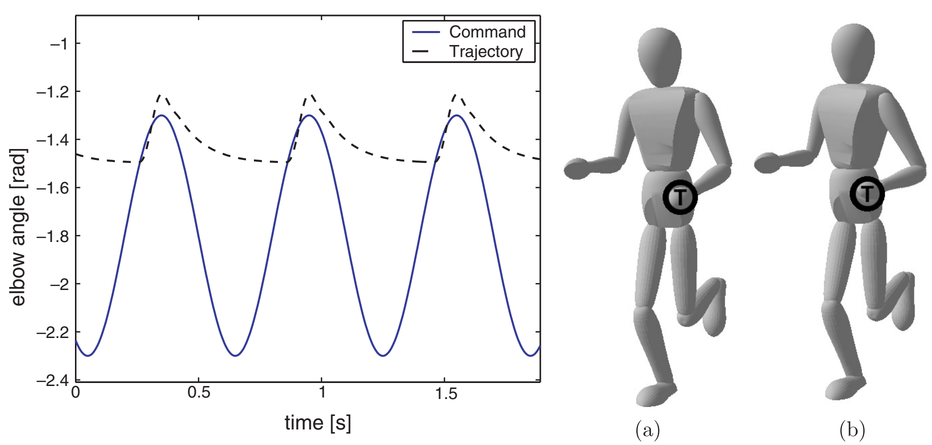


Fig. 5. **Non-Dynamically Consistent Control of a Feasible Posture:** The task consists of maintaining the hand position at **T** while the posture behavior oscillates the elbow in a sinusoidal manner. The poor performance results from the incorrect modeling for the task correction in the posture space.

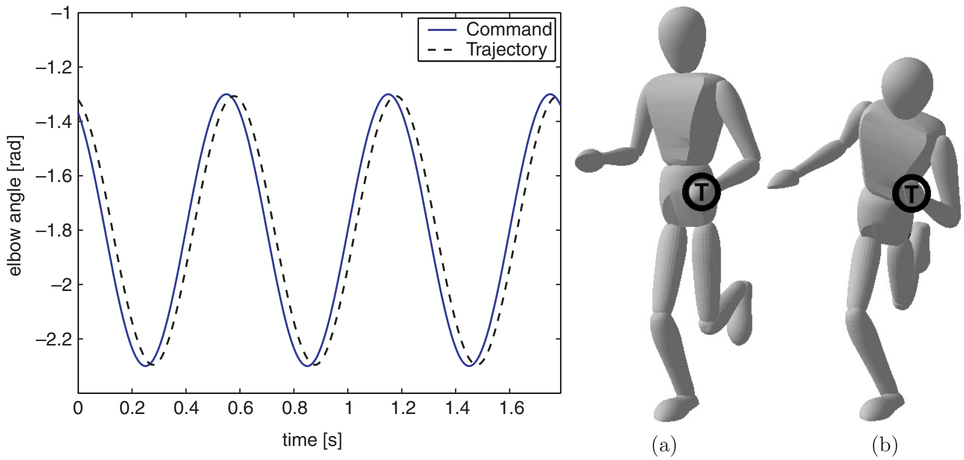


Fig. 6. **Dynamically Consistent Control of a Feasible Posture:** The task and posture are as in Fig. 5. By properly correcting for the influence of the task, the posture tracking is accurate.

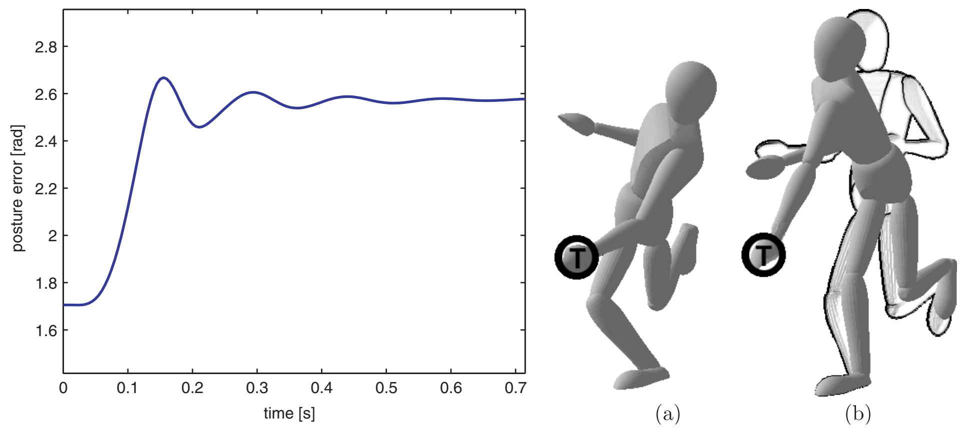


Fig. 7. **Non-Dynamically Consistent Control of a Conflicting Posture:** The task again fixes the hand location at **T** while the posture attempts to minimize the mean square error between the joint angles and a desired joint configuration outlined in (b). Improper task correction leads to poor posture performance, and the posture joint error increases from its starting configuration in (a).

5. Conclusion

To facilitate human interaction with human-like robots, these machines should move similarly to humans. Human motion is characterized by performing multiple tasks in a prioritized manner, and thus we need a robotic control framework that shares this behavior.

The operational space formulation and its extensions demonstrated that secondary tasks can be controlled without interfering with the primary task. In this

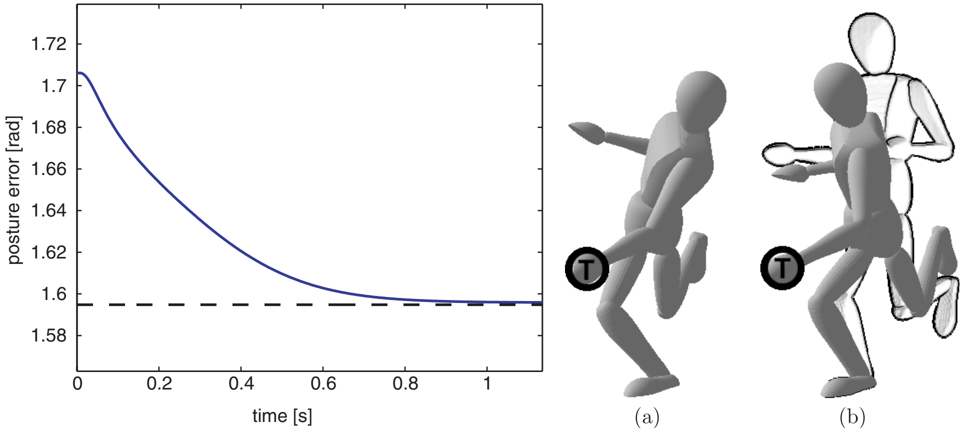


Fig. 8. **Dynamically Consistent Control of a Conflicting Posture:** The task and posture are the same as in Fig. 7. As a consequence of proper task correction, the posture joint error is locally minimized.

paper, we have introduced a task-dependent posture Jacobian that describes the kinematics of a secondary task within the task-associated posture space. Using this Jacobian, we have developed models of the dynamic behavior of secondary tasks within the posture space. These models have been included within the operational space formulation to provide a whole-body hierarchical control framework that independently compensates for the dynamics of each task.

Using our simulation environment, this framework has been verified through multiple experiments involving a collection of user-defined tasks. This paper has presented two control scenarios: one where the secondary task is consistent with the primary task, the other where the two tasks are not mutually feasible. For both scenarios, the new proposed controller attained significantly higher performance in comparison to a non-dynamically consistent posture controller.

As such, the development of models of subtask dynamic behavior within the posture space and the resulting dynamically consistent posture controller are vital steps in our research effort of mapping human behaviors for humanoid robot control.

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