

LEARNING DYNAMIC MOTOR SKILLS FOR VIRTUAL AND REAL HUMANOIDS

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LEARNING DYNAMIC MOTOR SKILLS FOR VIRTUAL AND REAL HUMANOIDS

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To myself,

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the only person worthy of my company.

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I want to “thank” my committee, without whose ridiculous demands, I would have graduated so, so, very much faster. Can I?

TABLE OF CONTENTS

DEDICATION	iii
ACKNOWLEDGEMENTS	iv
LIST OF TABLES	vii
LIST OF FIGURES	viii
SUMMARY	x
I INTRODUCTION	1
1.1 Falling Strategies for Humanoids	4
1.1.1 Falling and Landing Motion Control for Virtual Characters .	4
1.1.2 Multiple Contact Planning for Humanoids	5
1.2 Learning of Dynamic Controller for Characters	6
1.2.1 Iterative Design of Dynamic Controllers	6
1.2.2 Optimization with Failure Learning	7
1.2.3 Optimization for Parametrized Motor Skills	7
1.3 Model-based Learning for Virtual and Real Characters	7
1.4 Contributions	8
II RELATED WORK	10
2.1 Physics-based simulation of dynamic motor skills	10
2.1.1 Physics-based animation	10
2.1.2 Physics-based animation of highly dynamic motions	11
2.2 Control of falling motions	12
2.2.1 Falling detection techniques	12
2.2.2 Falling damage reduction strategies	12
2.2.3 Falling strategies of animals	13
2.3 Interactive interfaces	14
2.3.1 Parameter selection interfaces	14
2.3.2 Human-in-the-loop interfaces	14

2.4	Policy search algorithms	15
2.4.1	Model-free policy search algorithms	15
2.4.2	Model-based policy search algorithms	15
2.4.3	Policy search algorithms for parametrized tasks	17
III	FALLING AND LANDING MOTION CONTROL FOR VIRTUAL CHARACTERS	19
3.1	Motivation	20
3.2	Overview	22
3.3	Landing Strategy	23
3.4	Airborne Phase	26
3.5	Landing Phase	29
3.5.1	Impact Stage	30
3.5.2	Rolling Stage	32
3.5.3	Getting-Up Stage	33
3.6	Results	34
3.6.1	Evaluation	38
3.6.2	Limitations	39
3.7	Discussion	40
APPENDIX A	— SOME ANCILLARY STUFF	42
REFERENCES		43
INDEX		52
VITA		53

LIST OF TABLES

1	Control parameters.	32
2	Initial conditions of the examples shown in the video (in order of appearance)	35

LIST OF FIGURES

1	A falling motion of Parkour.	5
2	Hardware of BioloidGP robot.	5
3	The proposed learning frame uses human readable instructions to teach motions.	6
4	Bongo Board balance toy.	7
5	A cat is able to right itself as it falls to land on its feet, irrespective of its initial orientation.	13
6	Difference between a real robot and its simulation model results different motions from same controllers.	16
7	A simulated character lands on the roof of a car, leaps forward, dive-rolls on the sidewalk, and gets back on its feet, all in one continuous motion.	19
8	Three stages in the landing phase.	23
9	The left and middle are the desired landing poses for the hands-first strategy and the feet-first strategy, respectively. The right is the ready-to-roll pose for the feet-first strategy, which we track only the upper body.	24
10	Samples for hands-first landing strategy. Successful samples are bounded between top and bottom planes along $\theta^{(T)}$ axis. The middle plane, average of the two, indicates the linear relation of the ideal landing condition.	25
11	Samples in the space of $v_z^{(T)}$, $\omega_y^{(T)}$, and $\theta^{(T)}$. The spinning velocity $\omega_y^{(T)}$ has minimal effect on the success of a sample.	26
12	Among 16 poses in \mathbf{Q} , pose 1, 2, 9, and 13 are frequently selected by the airborne controller	29
13	Landing phase controller.	30
14	Two-step impact stage for the feet-first strategy.	31
15	Hands-first landing motion.	34
16	Left: The character model used for most examples. Right: A character with a disproportionately large torso and short legs.	37

17	Maximal stress for each joint from a hands-first landing motion. Results are quantitatively similar across all of our simulations. Green: Ragdoll motion. Blue: Our motion. Orange: Joint stress scaled by mass.	38
18	Feet-first landing motion.	40

SUMMARY

Summary goes here

CHAPTER I

INTRODUCTION

Over the last decades, humanoids become more available in academia, industry, and our daily life. They have played important roles as indefatigable workers in factories, surrogate rescue parties in disaster relief scenes, emotional friends in home [PEPPER], or virtual star sport players in computer games[EA]. And the recent development of software and hardware provides an opportunity to enrich their motion vocabularies with dynamic motor skills, which is essential for efficient and agile task achievements. One notable benefit of dynamic motions is that a humanoid can advance to desired locations as swift as possible using only its body, like a practitioner of free-running. Moreover, a humanoid can operate on the irregular terrain by overcoming obstacles with jumping and falling, which is often observed in disaster paces. Development of physics-based controllers for virtual and real humanoids are popular but yet challenging topics in many disciplines due to their large momentum and frequent changes of contacts. An in-depth understanding of mechanisms of dynamic motions and their controller would shed light on general motor control problems of humanoids.

Virtual characters and real robots are two main subjects of motor control problems in computer graphics and robotics, which have both common and different properties. To name a few common properties, control problems in both areas have non-linear objective function, under-actuated characters, high-dimensional control parameters. There are also different assumptions and limitations on sensors, actuators, contacts, control mechanisms, and so on. It is often possible to apply the existing principles and algorithms developed in one domain to the other and expedite the design process of the controller, if they are robust enough to handle different assumptions. For instance,

a virtual simulation of a robot is often used as a testbed for developing hardware compatible controllers due to the expensive cost and time-consuming trials [,,]. The techniques that are designed to control noisy hardware systems can be applied to virtual characters for creating more robust controllers. In this dissertation, I will develop control techniques for both virtual and real humanoids to demonstrate how the algorithms in two different systems can benefit each other.

Highly dynamic motor skills are difficult tasks for humanoids. Execution of dynamic motions accompanies abrupt accelerations and decelerations of momentum, frequent changes of contacts, and explosive usage of torques near limitations. Therefore, control becomes a very sensitive problem because small errors can quickly accumulate and generate a disastrous result to the humanoid, such as loosing it balance and hitting the ground severely. One of challenging motions is safe falling of a humanoid, which is a fundamental motor skill that protects the subject from severe injuries and connects the previous and next actions for fluent transitions. A falling motion requires very accurate control because a robot must decelerate huge vertical momentum within a fraction of a second, and a minor failure will cause huge damage to the body parts. In addition, a wide range of initial conditions must be considered for robustness because falling can be initiated by unexpected situations. The development of falling controllers will make virtual characters and robots to execute motions safely and smoothly, and its principles can be applied to the other highly dynamic motions with huge momentum.

There are several issues when a user develops physics-based controllers for difficult dynamic motor skills. The first problem arises when the user designs objectives, control mechanisms, and control parameters, which require a lot of prior knowledge. Since a large portion of controller designs remains unknown until testing the implementation, the design process is often driven by trial-and-errors. This can be very

tedious and time-consuming, especially in the traditional monolithic optimization setting that may take several hours to days. Thus, it is important to develop a simple and intuitive design process that allows the user to train controllers within a short amount of time. An iterative learning can be more efficient due to short feedback loops that can easily test and modify the controller, and more intuitive because it is similar how human learn motor skills through progressive process of coaching and practicing.

Optimizing control parameters for dynamic motions is another time-consuming step that requires a lot of computing power. Typically, whole-body dynamic tasks typically have a cost function that is multimodal, non-linear, non-convex, and discontinuous due to an under-actuated system and discrete contacts. Further, control parameters are likely to be in a high dimensional space with small feasible regions that does not generate undesired behaviors. These difficulties often require the most robust optimization algorithm. In computer animation, a robust black-box sampling-based method, Covariance Matrix Adaption Evolution Strategy (CMA-ES) [], has been frequently applied to discontinuous control problems, such as biped locomotion [], parkour-style stunts[], or swimming []. However, CMA-ES is not the most effective algorithm for optimizing dynamic motor skills when they have small feasible regions or high-dimensional control space due to the parametrization. This motivated me to work on improving the performance of the baseline algorithm, CMA-ES, for more difficult tasks with many user constraints I further extend CMA-ES for a parametrized motor skill, which is essential for operating a robot in the unpredictable environment.

Unlike the optimization for virtual characters, a control policy search for hardware with many trials is often infeasible because conducting hardware experiment can be expensive and time-consuming. Moreover, an execution of a bad controller on a robot can potentially cause disastrous damage to the robot and enormous cost to repair. To reduce the number of trials on the hardware, a virtual simulation is

used as a practical solution that provides a fast and safe evaluation of the control parameters. However, it suffers from *simulation bias* in which controllers developed for a virtual character do not work on hardware due to differences in the two systems. The *simulation bias* is hard to explicitly model because it can be caused by many reasons, such as different mass-distributions, sensor and actuator noises, command delays, and more. Therefore, a data-driven model-based policy search, which iteratively updates the simulation using collected hardware data, is a promising method to model the simulation bias, which will be discussed in this dissertation.

I will present the following identified problems for developing controllers for highly dynamic motor skills.

1.1 Falling Strategies for Humanoids

Highly dynamic motions often accompany the abrupt momentum changes, which can cause large contact forces to characters. Therefore, how to manage falls is a fundamental motor skill to reduce damages to humanoids and achieve fluent transitions between motor skills. In this dissertation, I will discuss two different falling scenarios, for virtual and real humanoids. For a virtual character, I will describe a general controller that allows the character to fall from a wide range of heights and initial speed, which are inspired by falling of traceurs. For a real robot, a general falling strategy for handling various external perturbations is introduced, which is feasible to be executed by actual hardware. The effectiveness of the presented strategies will be validated in physics simulation, and experimentally tested on a small-size humanoid.

1.1.1 Falling and Landing Motion Control for Virtual Characters

In Chapter 3, I will show how to create an on-line controller for generating agile and natural falling motions of the virtual character that can land from various heights and velocities. The goals of the controller are to reduce the joint stress at the impact and get back on its feet to prepare the next action.

Inspired by falling skills of Parkour (Figure 1), I formulate the falling problem with three phases, *airborne*, *impact*, and *rolling* based on the contact states. First, two sub-controllers are designed for the *airborne* and *rolling* phases and a regression analysis is conducted to find an optimal landing angle that can connect two sub controllers at the *impact* phase. I will demonstrate that the motion generated by the proposed controller induces smaller joint stress, which is still four times lower than a rag-doll motion at the worst cases.

1.1.2 Multiple Contact Planning for Humanoids

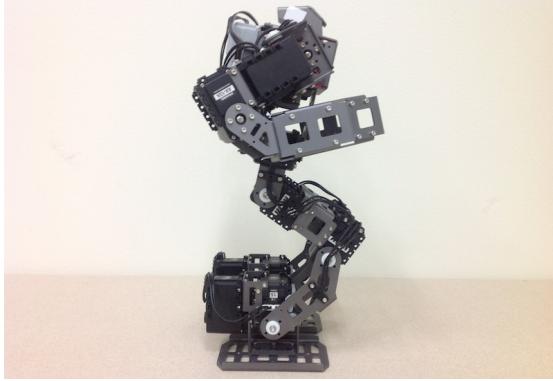


Figure 2: Hardware of BioloidGP robot.



Figure 1: A falling motion of Parkour.

Chapter 4 will describe a general algorithm which plans for appropriate responses to a wide variety of falls, from a single step to recover a gentle nudge, to a rolling motion to break a high-speed fall. Our multiple contact planning provides a unified framework that can represent many existing falling techniques [,,].

Then, I will show how to efficiently optimize the multiple contact falling strategy to the given initial state using a simplified model and dynamic programming. Finally, various scenarios will be tested on simulated humanoids and the actual hardware (Figure 2) to show that our algorithm plans various falling strategies with different contact sequences.

1.2 Learning of Dynamic Controller for Characters

Teaching a physically simulated character a new motor skill requires a lot of efforts from the controller designer, from the design of the control mechanism to the tweaking of low-level control parameters. To simplify the learning process, I will introduce an intuitive and interactive framework for developing dynamic controllers that is inspired by how humans learn dynamic motor skills through a iterative process of coaching and practicing. Further, we propose two optimization techniques that can extend the popular policy search algorithm, CMA-ES, to accelerate the convergence rate and to optimize a parametrized objective function.

1.2.1 Iterative Design of Dynamic Controllers

In Chapter 5, I will describe an iterative framework to design dynamic controllers using high-level, human-readable instructions, inspired by a training process of athletes that consists of interactive coaching and repetitive practices (Figure 3) To enable interactive coaching, I introduce “control rigs” as an in-

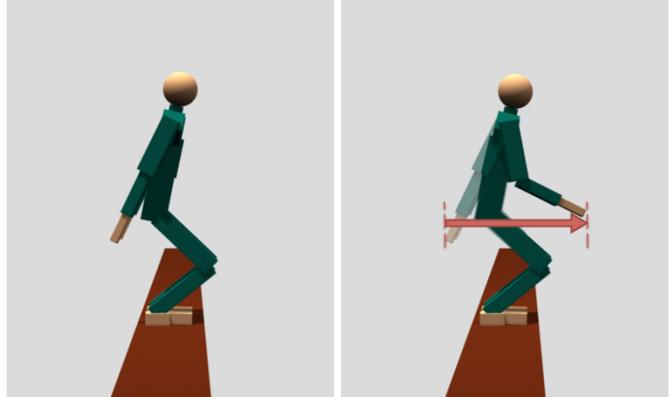


Figure 3: The proposed learning frame uses human readable instructions to teach motions.

termediate layer of control module to facilitate the mapping between human instructions and low-level control parameters. During the practicing stage, control parameters are efficiently determined using CMA-ES, which will be further improved in the following chapters. The details of controllers development process using our iterative learning framework will be shown with example parkour motions.

1.2.2 Optimization with Failure Learning

A controller with many user constraints is difficult to optimize due to the relatively small feasible region. In Chapter 6, I will describe a new optimization algorithm for highly-constrained problems based on the observation of humans ability to learn from failure. The proposed algorithm, CMA-C (Covariance Matrix Adaptation with Classification) utilizes the failed simulation trials to approximate an infeasible region in the space of control rig parameters so that it can predict the quality of the samples, resulting a faster convergence than the standard CMA-ES.

1.2.3 Optimization for Parametrized Motor Skills

In Chapter 7, I will explain the optimization of parametrized motor skills. The parametrization of the learned motor skills is an essential ability because a robot can reinterpret the skill to a new situation, without learning from scratch. Instead of maintaining a single Gaussian distribution, the algorithm reduces the number of samples by evolving a parametrized probability distribution for a range of skills. I will test the algorithm on a simulated humanoid robot learning three parametrized dynamic motor skills, including vertical jump, kick a ball, and walk.

1.3 Model-based Learning for Virtual and Real Characters



Figure 4: Bongo Board balance toy.

In Chapter 8, I will describe an iterative approach for learning hardware models and optimizing control policies with as few hardware experiments as possible. Instead of learning hardware models from scratch, the proposed approach only learns the difference from a simulation model. Similarly to the previous

work, Gaussian Process is used to model the difference between dynamics of virtual and real characters based on the collected hardware data. To prove the concept, I will validate the algorithm on two different simulation models, one with perfect contacts and one with realistic contacts, by finding a balancing controller for a bipedal robot on a bongo board (Figure 4).

1.4 Contributions

The control and optimization methods discussed in this dissertation provide several contributions to the computer animation community. These contributions are as follows:

- **A falling and landing strategy for virtual characters** The falling strategy presented in the dissertation allows the character to fall from a wide range of heights and initial speeds, continuously roll on the ground, and get back on its feet, without inducing large stress on joints at any moment.
- **A multiple contact falling strategy for robots** I also introduce a new falling strategy that can optimize a sequence of contacts, which optimizes the number and locations of contacts for the given initial state.
- **An iterative learning framework for dynamic motor skills** Unlike previous monolithic design processes in the literature, I proposed an iterative and interactive learning framework using human readable instructions. Starting from a basic controller, the proposed framework allows a user to easily train complex dynamic motion controllers within minutes, with only a few high-level instructions from the user.
- **An optimization technique for highly constrained problems** I introduce a novel efficient optimization algorithm, CMA-C, that is designed for the problem with many constraints and smaller feasible regions. The algorithm

converges faster than the standard CMA-ES, by approximating the infeasible region using Supported Vector Machines.

- **An optimization technique for parametrized tasks** I introduce an efficient evolutionary optimization algorithm for learning parametrized skills to achieve whole-body dynamic tasks, which is much faster than the baseline algorithm, CMA-ES.
- **A model-based policy search for reducing hardware experiments** I propose an iterative approach for learning hardware model and optimizing policies with as few hardware experiments as possible by learning the difference between a simulation model and hardware.

In the next chapter, I will discuss the related work conducted by other researchers to address similar problems.

CHAPTER II

RELATED WORK

In this section, I will review relevant previous work done in computer graphics, robotics, and bio-mechanics. In Section 2.1, I will start with a brief introduction on popular animation techniques to generate highly dynamic motions of biped characters in the physics-based simulation. In Section 2.2, I will review previous methods for controlling falling motions of humanoids to reduce damage to body parts. In Section 2.3, I will briefly summarize prior interactive interfaces for selecting parameters, especially under the *human-in-the-loop optimization* paradigm, which is adopted in this dissertation for incorporating interactive user interventions in a controller design process. In Section 2.4, I will review various policy search techniques and optimization algorithms in both computer graphics and robotics that find optimal control parameters for humanoids.

2.1 *Physics-based simulation of dynamic motor skills*

2.1.1 Physics-based animation

Physics-based character animation is a promising approach to creating realistic and interactive animations, but designing controllers remains difficult largely due to the complex relationship between the control and the state variables. Early work [28, 96] demonstrated that a variety of motions can be achieved by controlling the individual joints with manually designed state machines. Since this seminal work was published, researchers in computer animation have been searching for new control algorithms that are more robust, more generalizable, and more automatic. Using motion capture data for reference trajectories was a step toward a more automatic process for controller design [103, 77], however, the simulated motions cannot deviate much

from the input data. An improved approach applied linear or nonlinear quadratic regulators to track reference trajectories, leading to more robust controllers against perturbations [14, 58]. Combination of PD servos and a specialized balance controller driven by a simple state machine was a very successful strategy [99], which enabled much follow-on work in biped control [89, 8, 42, 32]. Global planning of momentum has also been applied to a wide range of motion from standing balance [48] to locomotion [54, 98] to highly dynamic motion [25, 46, 3, 102]. Coros *et al.* adopted Jacobian transpose control from robotics literature [83] to generate stable biped and quadruped locomotion [8, 9]. Ha *et al.* further demonstrated the effectiveness of the Jacobian transpose control on dynamic stunts [47, 25, 24].

2.1.2 Physics-based animation of highly dynamic motions

Previous work has demonstrated that highly dynamic motions with a long ballistic phase can be synthesized using physics simulation or kinematic approaches. Hodgins *et al.* [28, 96] showed that carefully crafted control algorithms can simulate highly athletic motions, including diving, tumbling, vaulting, and leaping. Faloutsos *et al.* [17] composed primitive controllers to simulate more complex motor skills, such as a kip-up move or a dive down stairs. Liu *et al.* [47] successfully tracked contact-rich mocap sequences using a sampling-based approach. They showed that vigorous motions with complex contacts, such as a dive-roll or a kip-up move, can be dynamically simulated, provided full body mocap sequences as desired trajectories. Zhao and van de Panne [101] provided a palette of parametrized actions to build a user interface for controlling highly dynamic animation. Other techniques directly edit ballistic motion sequences under the constraints imposed by conservation of momentum [49, 78], or apply a hybrid method for synthesizing dynamic response to perturbation in the environment [75]. If the contact positions and timing are known, spacetime optimization techniques can also generate compelling dynamic motions [45, 18, 72, 82]. This thesis

the approach of physical simulation, but I seek for a more general and robust control algorithm such that the controller can operate under a wide range of initial conditions and allow for runtime perturbations.

2.2 *Control of falling motions*

2.2.1 Falling detection techniques

To activate a falling controller, a robot first predicts a fall and try to recover the balance if it is possible. Various machine learning techniques has been proposed to detect falls, such as Principal Component Analysis [34] or Supported Vector Machine [36]. Horn and Gerth [29] detects unstable situations with Gaussian Mixture Model or Hidden Markov Model and activates appropriate reflex controls, such as crouching. Renner and Benke [67] proposed to detect instability using an aggregated sensor deviation and stabilize the gait with manually designed reflex controllers. The falling strategies presented in this dissertation focus on control of falling motions to reduce damage when the robot detects falling, presumably with one of the above techniques.

2.2.2 Falling damage reduction strategies

When a robot is pushed hard and falling is inevitable, various techniques has been proposed to minimize damage on humanoid. Fujiwara *et al.* [21, 22, 20, 19] proposed falling techniques inspired by Japanese martial arts (*Ukemi*). Ogata *et al.* [62, 61] evaluates the risk of falling with predicted ZMP and optimizes COM trajectories to reduce damage. Ruiz-del-Solar *et al.* [71, 70] designed low damage falling sequences for soccer robots and verified them in the simulation. Wang *et al.* [92] formulated an optimization of whole body trajectories as a nonlinear programming problem and solved it with heuristics. Lee and Goswami [41] proposed a control strategy that reorients the robot to fall with a backpack for absorbing shock. Yun and Goswami [100] addressed a “tripod” strategy that stops with a swing foot and two hands to

maintain the final COM location higher from the floor. To protect the surrounding environment, [23] proposed a fall direction-changing strategy that utilizes foot placement and inertia shaping.

In contrast to the related work for falls caused by external perturbations, there are more works that focus on falls from higher places. In those cases, control strategies during long airborne phase become critical for safe landing. I draw inspiration from kinesiology literature and sport practitioners. In particular, the techniques developed in freerunning and parkour community are of paramount importance for designing landing control algorithms capable of handling arbitrary scenarios [16, 30]. In robotics, Bingham *et al.* [5] proposed an algorithm that leverages nonholonomic trajectory planning inspired by the falling cat to orient an articulated robot through configuration changes to achieve a pose that reduces the impact at landing.

2.2.3 Falling strategies of animals

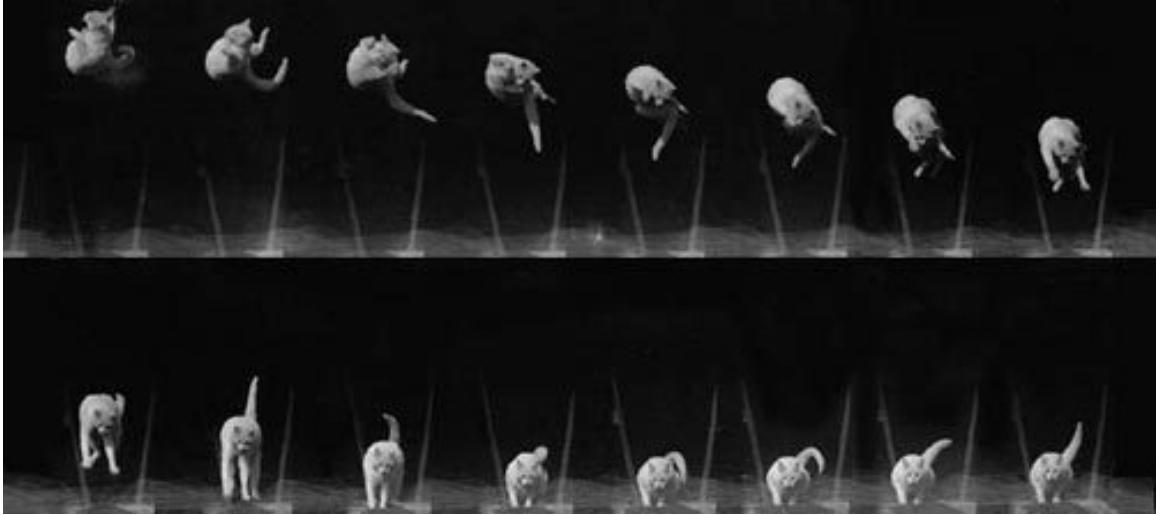


Figure 5: A cat is able to right itself as it falls to land on its feet, irrespective of its initial orientation.

Many animals have astonishing capabilities to achieve different maneuvers in the air by manipulating their body articulations. Cats are known for landing with feet from any initial falling condition [33, 52, 73] (Figure 5). Lizards swing their tails

to stabilize their bodies during a leap [43]. Pigeons reorient their bodies to achieve a sharp turn when flying at low speed [68]. These behaviors inspire scientists and engineers to develop intelligent devices and control algorithms. This dissertation has a similar goal that we study how human body can change shape in the air to reduce damage at landing.

2.3 *Interactive interfaces*

2.3.1 Parameter selection interfaces

A common approach in parameter selection interfaces is to present the parameter space (or a collection of samples thereof) in an explorable way, through 2D layout of results [50]; careful selection of sliders [63, 44]; or (in a physics context) direct manipulation [65] or in-situ visualization [87]. Both [93, 94] represent simulations as tracks (or word lines) where each parameter change corresponds to branches that spawn new tracks, and [93] describes how to incorporate uncertain parameter values into this exploratory visualization. Meanwhile [6] clusters outcomes from different timelines to suppress minor variations and to highlight entire outcome categories. These methods help a designer understand the effects of parameter variation on a single set of initial conditions.

2.3.2 Human-in-the-loop interfaces

Without human guidance, fully automated optimization algorithms sometimes produce undesired solutions due to unexpected factors or situations. To fill the gap, researchers have developed semi-automatic systems which involve a human in the process to provide prior knowledge and guidance to the optimization. [74]. This type of optimization systems, called *human-in-the-loop* (HITL) optimization, have proven effective for various problems, such as vehicle planning [95] or interface optimization [66]. The level of user interaction varies from simply selecting of the generated solutions [76] to directly editing the search parameters and constraints [79]. Unlike

most previous work which primarily focused on developing user interaction and visualization techniques for HITL optimization systems, I develop a new controller design framework that exploit the nature of HITL computation paradigm.

2.4 *Policy search algorithms*

2.4.1 Model-free policy search algorithms

In robotics, a common techniques for searching optimal policy parameters is model-free policy optimization, where the policy is improved through a number of hardware trials [55, 39]. Unfortunately, these methods generally require hundreds of trials, which is unrealistic for tasks such as humanoid balancing and locomotion. One way to overcome this issue is to limit the parameter space by using task-specific primitives [59] or to provide a good initial trajectory by human demonstration [4]. However, it is not clear how to extend these approaches to dynamically unstable robots or tasks that cannot described by joint trajectories.

Various optimization techniques have been applied to improve the motion quality or the robustness of the controller. In character animation, a sampling-based method, Covariance Matrix Adaption Evolution Strategy (CMA-ES) [26], has been frequently applied to discontinuous control problems, such as biped locomotion [89, 90, 91], parkour-style stunts[46, 24], or swimming [85]. To compensate the expensive cost of sampling-based algorithm, different approaches have been proposed, including exploiting the domain knowledge [89, 90, 91], shortening the problem horizons [77], or using a classifier to exclude infeasible samples [24]. Based on the previous success of CMA-ES, I proposed new sampling-based algorithms that resemble the evolution process of distribution.

2.4.2 Model-based policy search algorithms

Difference between a robot and its simulation model becomes a serious problem when we try to use controllers obtained by model-based optimization or tuned in simulation

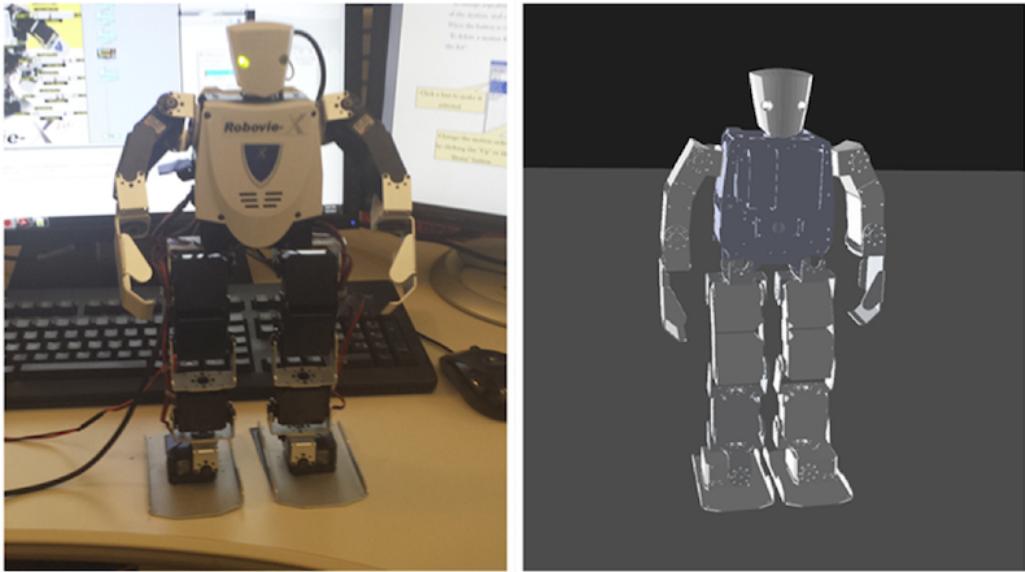


Figure 6: Difference between a real robot and its simulation model results different motions from same controllers.

(Figure 6). Classical parameter identification techniques [35] partially solve this problem by fitting model parameters to experimental data, but they are still limited to factors that can actually be modeled. Furthermore, these approaches assume that the data set is large enough to accurately estimate the parameters. In large and unstable systems such as humanoid robots, it is often difficult to collect enough data [97].

A number of researchers have attempted to overcome the drawbacks of these approaches by combining simulation and real-world data [84, 53, 64]. Abbeel et al. [1] used an inaccurate model to estimate the derivative of the cost with respect to the policy parameters. Ko et al. [37] used Gaussian Process to model the difference between a nonlinear dynamics model and the actual dynamics and applied the model to reinforcement learning for yaw control of a blimp. However, they do not iterate the process to refine the model. Deisenroth et al. [15] also used Gaussian Process for learning the dynamics model from scratch. Similarly, Morimoto et al. [56] used Gaussian Process for learning simplified dynamics of human locomotion. Sugimoto et al. [81] used *sparse pseudo-input Gaussian Process* (SPGP) that accounts both

variances of inputs and outputs to handle sensor noises. Instead, Tangkaratt et al. [86] used *least-squares conditional density estimation* (LSCDE) to learn the dynamics model without Gaussian assumption on the transitions. Cutler et al. [10] trained a policy in multiple fidelity simulators with discretized actions. Ross and Bagnell [69] theoretically proved that their iterative system identification method converges even the system is not in the assumed class. Please refer to Section 6 of [38] for more complete survey on this topic.

2.4.3 Policy search algorithms for parametrized tasks

There is a large body of research work on generalization of learned motor skills to achieve new tasks. da Silva *et al.* [13, 11, 12] introduced a framework to represent the policies of related tasks as a lower-dimensional piecewise-smooth manifold. Their method also classifies example tasks into disjoint lower-dimensional charts and model different sub-skills separately. Much research aimed to generalize example trajectories to new situations using dynamic movement primitives (DMPs) to represent control policies [31]. A DMP defines a form of control policies which consists of a feedback term and a feedforward forcing term. Ude *et al.* [88] used supervised learning to train a set of DMPs for various tasks and built a regression model to map task parameters to the policy parameters in DMPs. Muelling *et al.* [57] proposed a mixture of DMPs and used a gate network to activate the appropriate primitive for the given target parameters. Kober *et al.* [40] trained a mapping between task parameters and meta-parameters in DMPs using a cost-regularized kernel regression. Through reinforcement learning framework, they computed a policy which is a probability distribution over meta-parameters. Matsubara *et al.* [51] trained a parametric DMP by shaping a parametric-attractor landscape from multiple demonstrations. Stulp *et al.* [80] proposed to integrate the task parameters as part of the function approximator of

the DMP, resulting in more compact model representation which allows for more flexible regression. Neumann *et al.* [60] modified the existing learning algorithm (REPS) to learn a hierarchical controller that has parameterized options.

All these methods described above depend on collecting a set of examples. This presents a bottleneck to learning because an individual control policy needs to be learned for each task example drawn from the distribution of interest. da Silva *et al.* further proposed using unsuccessful policies as additional training samples to accelerate the learning process [11]. For dynamic motor skills which involve intricate balance tasks, unsuccessful policies generated during training a particular task are of no use to other tasks because they often lead to falling motion. Hausknecht *et al.* [27] demonstrated a quadruped robot kicking a ball to various distances, but whole-body balance was not considered in their work. Another challenge regarding dynamic tasks is that each task can be achieved by a variety of policies, some of which might be overfitting the task. Interpolating these overfitted policies can lead to unexpected results. In this dissertation, I proposed a new algorithm that tends to generate more coherent mapping between task parameters and policy parameters because we simultaneously learn the policies for the entire range of the tasks.

The next chapter will describe falling strategies for virtual characters and real robots, which are essential for protecting humanoids from severe damage.

CHAPTER III

FALLING AND LANDING MOTION CONTROL FOR VIRTUAL CHARACTERS



Figure 7: A simulated character lands on the roof of a car, leaps forward, dive-rolls on the sidewalk, and gets back on its feet, all in one continuous motion.

This chapter introduces a new method to generate agile and natural human landing motions in real-time via physical simulation without using any mocap or pre-sketched sequences. We develop a general controller that allows the character to fall from a wide range of heights and initial speeds, continuously roll on the ground, and get back on its feet, without inducing large stress on joints at any moment. The character’s motion is generated through a forward simulator and a control algorithm that consists of an airborne phase and a landing phase. During the airborne phase, the character optimizes its moment of inertia to meet the ideal relation between the landing velocity and the angle of attack, under the laws of conservation of momentum. The landing phase can be divided into three stages: impact, rolling, and getting-up. To reduce joint stress at landing, the character leverages contact forces to control linear momentum and angular momentum, resulting in a rolling motion which distributes impact over multiple body parts. We demonstrate that our control algorithm can be applied to a variety of initial conditions with different falling heights, orientations, and linear and angular velocities. Simulated results show that our algorithm

can effectively create realistic action sequences comparable to real world footage of experienced freerunners.

3.1 Motivation

One of the great challenges in computer animation is to physically simulate a virtual character performing highly dynamic motion with agility and grace. A wide variety of athletic movements, such as acrobatics or freerunning (parkour), involve frequent transitions between airborne and ground-contact phases. How to land properly to break a fall is therefore a fundamental skill athletes must acquire. A successful landing should minimize the risk of injury and disruption of momentum because the quality of performance largely depends on the athlete’s ability to safely absorb the shock at landing, while maintaining readiness for the next action. To achieve a successful landing, the athlete must plan coordinated movements in the air, control contacting body parts at landing, and execute fluid follow-through motion. The basic building blocks of these motor skills can be widely used in other sports that involve controlled falling and rolling, such as diving, gymnastics, judo, or wrestling.

We introduce a new method to generate agile and natural human falling and landing motions in real-time via physical simulation without using motion capture data or pre-scripted animation (Figure 7). We develop a general controller that allows the character to fall from a wide range of heights and initial speeds, continuously roll on the ground, and get back on its feet, without inducing large stress on joints at any moment. Previous controllers for acrobat-like motions either precisely define the sequence of actions and contact states in a state-machine structure, or directly track a specific motion capture sequence. Both cases fall short of creating a generic controller capable of handling a wide variety of initial conditions, overcoming drastic perturbations in runtime, and exploiting unpredictable contacts.

Our method is inspired by three landing principles informally developed in freerunning community. First, reaching the ground with flexible arms or legs provides cushion time to dissipate energy over a longer time window rather than absorbing it instantly at impact. It also protects the important and fragile body parts, such as the head, the pelvis, and the tailbone. Second, it is advisable to distribute the landing impact over multiple body parts to reduce stress on any particular joint. Third, it is crucial to utilize the friction force generated by landing impact to steer the forward direction and control the angular momentum for rolling, a technique referred to as "blocking" in the freerunning community. These three principles outline the most commonly employed landing strategy in practice: landing with feet or hands as the first point of contact, gradually lowering the center of mass (COM) to absorb vertical impact, and turning a fall into a roll on the ground, with the head tightly tucked at impact moment.

However, translating these principles to control algorithms in a physical simulation is very challenging. During airborne, the controller needs to plan and achieve the desired first point of contact and the angle of attack, in the absence of control over the characters global motion in the air. Instead of solving a large, nonconvex two-point boundary value problem, we develop a compact abstract model which can be simulated efficiently for real-time applications. To strike the balance between accuracy and efficiency, our algorithm replans the motion frequently to compensate the approximation due to the simplicity of the model. When the character reaches the ground, the controller needs to take a series of coordinated actions involving active changes of contact points over a large area of human body. Our algorithm executes three consecutive stages, impact, rolling, and getting-up by controlling poses, momentum, and contacts at key moments. Furthermore, the airborne and landing phases are interrelated and cannot be considered in isolation: the condition for a successful landing defines the control goals for the airborne phase while the actions taken during

airborne directly impact the landing motion. We approach this problem in a reverse order of the action sequence: designing a robust landing controller, deriving a successful landing condition from this controller, and developing an airborne controller to achieve the landing condition.

We demonstrate that our control algorithm is general, efficient, and robust. We apply our algorithm to a variety of initial conditions with different falling heights, orientations, and linear and angular velocities. Because the motion is simulated in real-time, users can apply perturbation forces to alter the course of the character in the air. Our algorithm is able to efficiently update the plan for landing given the new situations. We also demonstrate different strategies to absorb impact, such as a dive roll, a forward roll, or tumbling. The same control algorithm can be applied to characters with very different body structures and mass distributions. We show that a character with unusual body shape can land and roll successfully. Finally, our experiments empirically showed that the algorithm induces smaller joint stress, except for the contacting end-effectors. In the worst case of our experiments, the average joint stress is still four times lower than landing as a passive ragdoll.

3.2 Overview

We introduce a physics-based technique to simulate strategic falling and landing motions from a wide range of initial conditions. Our control algorithm reduces joint stress due to landing impact and allows the character to efficiently recover from the fall. The character’s motion is generated through a forward simulator and a control algorithm that consists of an *airborne phase* and a *landing phase*. These two phases are related by an appropriate *landing strategy*, which describes the body parts used for the first contact with the ground, a desired landing pose, and an ideal landing condition that describes the relation between landing velocities and the angle of attack in successful landing motions. We develop two most common types of landing

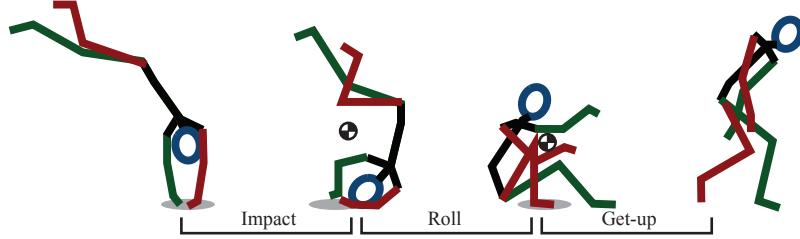


Figure 8: Three stages in the landing phase.

strategies: hands-first and feet-first, and introduce a sampling method to derive the ideal landing condition for each strategy.

At the beginning of a fall, the character first decides on a landing strategy. During the airborne phase, the character optimizes its moment of inertia to achieve the ideal landing condition. The landing phase is divided into three stages: impact, rolling, and getting-up (Figure 8). The impact stage begins when the character reaches the ground. During the impact stage, the character leverages the friction forces from the ground to control linear and angular momentum. After the COM moves beyond the hand contact area, the character switches to the rolling stage in which continuous change of contact carries out. In preparation for standing up, the character needs to maintain the rolling direction and plant its feet on the ground. When the COM passes through the first foot, the character starts to elevate the COM in order to complete the landing process in an upright position.

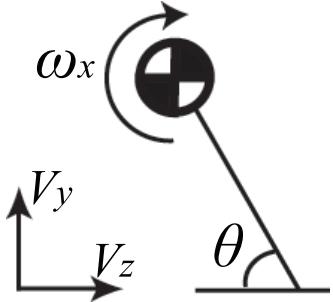
3.3 Landing Strategy

Given an initial condition at the beginning of a fall, the character can choose to land with the hands-first strategy or the feet-first strategy. In general, the hands-first strategy is chosen only for aesthetics purpose because it is less robust and suitable only for falls with planar angular momentum (about the pitch axis). In contrast, the feet-first strategy can handle a wide range of arbitrary initial conditions because it includes an extensive foot-ground contact duration to modulate the momentum before

rolling. A landing strategy also includes a desired landing pose. Our algorithm only requires a partial pose to stretch the arms or legs at landing, depending on whether the hands-first or the feet-first strategy is chosen. We manually specify this partial pose for each strategy (Figure 9).



Figure 9: The left and middle are the desired landing poses for the hands-first strategy and the feet-first strategy, respectively. The right is the ready-to-roll pose for the feet-first strategy, which we track only the upper body.



An integral part of our landing strategy is the landing condition, a simple equation that compactly characterizes successful landing motions. If the character manages to turn a fall into a roll and gets back on its feet at the end of the roll, we consider it successful. Because a successful landing highly depends on whether the character is able to control the momentum at the moment of the first contact (T), our algorithm defines the landing condition as a relation between the global linear velocity $\mathbf{v}^{(T)}$, global angular velocity $\omega^{(T)}$, and the angle of attack $\theta^{(T)}$, which approximates the global orientation of the character. The actual coefficients of the landing condition depend on the design of the landing controller, which cannot be derived analytically, but can be learned from examples generated by the landing controller. We apply a sampling method, similar in spirit to the approach Coros *et al.* [7] presented for biped locomotion, to determine the landing condition for a particular landing strategy.

For the hands-first strategy with planar motion, we consider a four-dimensional space spanned by $\theta^{(T)}$, $v_y^{(T)}$, $v_z^{(T)}$ and $\omega_x^{(T)}$. Given a sample in the parameter space, we

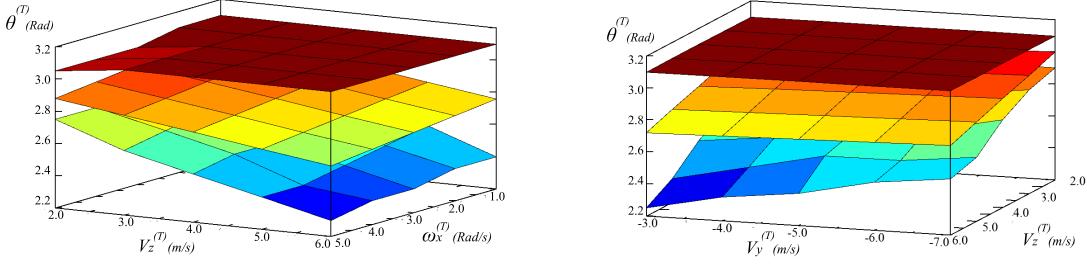


Figure 10: Samples for hands-first landing strategy. Successful samples are bounded between top and bottom planes along $\theta^{(T)}$ axis. The middle plane, average of the two, indicates the linear relation of the ideal landing condition.

run our landing controller to test whether the character can successfully get up at the end. Empirical results from thousands of random samples show that the successful region is mostly continuous and linear (Figure 10). We can bound the successful samples in the $\theta^{(T)}$ axis using two hyperplanes. Taking the average of the maximum and the minimum planes, we derive a linear relation between the angle of attack and the landing velocities as

$$\theta^{(T)} = a v_y^{(T)} + b v_z^{(T)} + c \omega_x^{(T)} + d \quad (1)$$

where a , b , c , and d are the coefficients of the fitted hyperplane. Note that Equation (1) is a sufficient but not necessary condition for successful landing. Most points between the maximal and minimal hyperplanes also lead to successful landing motions. This means that even when the character cannot meet the landing condition exactly, it still has a good chance to land successfully. For the feet-first strategy, in theory, we need to consider all six dimensions of linear velocity and angular velocity. However, our empirical results show that non-planar velocities do not affect $\theta^{(T)}$ as long as they stay within a reasonable bound (Figure 11). As a result, the feet-first strategy is able to handle non-planer falling motion using the same parameters (but different coefficients) in Equation (1).

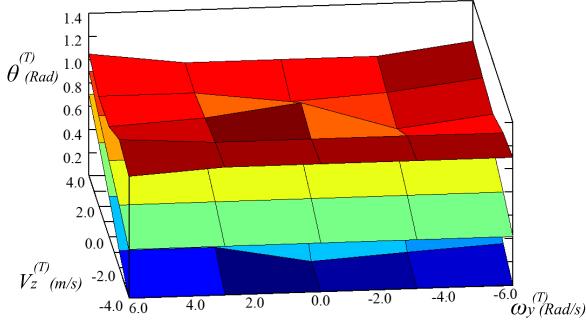


Figure 11: Samples in the space of $v_z^{(T)}$, $\omega_y^{(T)}$, and $\theta^{(T)}$. The spinning velocity $\omega_y^{(T)}$ has minimal effect on the success of a sample.

3.4 Airborne Phase

Once the character decides on a landing strategy, the goal of the airborne phase is to achieve the corresponding landing pose and landing condition. Because momentum is conserved in air, the linear velocity, the total airborne time T , as well as the angular momentum are already determined by the initial condition of the fall. However, the character can still control the angular velocity $\omega_x^{(T)}$ and the angle of attack $\theta^{(T)}$ by varying its pose (i.e. actuated degrees of freedom (DOFs) excluding the global position and orientation) to change the moment of inertia. To most effectively achieve the desired landing condition, we design our airborne algorithm based on the strategy employed in platform diving competition, where a highly trained athlete performs a sequence of predefined poses to manipulate the final orientation and angular velocity.

To this end, our airborne controller uses a PD servo to track a sequence of poses that lead to the ideal landing condition. The sequence of poses is replanned frequently to correct the errors caused by perturbation and numerical approximation. Each time the algorithm makes a new plan, an optimal sequence of poses from the current moment to the landing moment is computed. This sequence starts with the current pose \mathbf{q}_0 and ends at the desired landing pose \mathbf{q}_T (determined by the landing strategy), with a duration of T seconds. Our control algorithm searches for an intermediate pose \mathbf{q}^* and a duration Δt^* , such that the character can reach the ideal landing condition by

changing to \mathbf{q}^* immediately and holding the pose \mathbf{q}^* for Δt^* seconds before changing to the final pose \mathbf{q}_T .

We formulate an optimization to solve for an intermediate pose \mathbf{q} and its holding duration Δt that can best achieve the ideal landing condition. The cost function $g(\mathbf{q}, \Delta t)$ is defined in Equation 2.

$$g(\mathbf{q}, \Delta t) = \theta^{(T)}(\mathbf{q}, \Delta t) - a v_y^{(T)} - b v_z^{(T)} - c \omega_x^{(T)}(\theta^{(T)}) - d \quad (2)$$

Note that $\omega_x^{(T)}$ is a function of $\theta^{(T)}$ because we need global orientation of the character at time T to compute the global angular velocity. If we can compute $\theta^{(T)}$, Equation (2) can be readily evaluated. Unfortunately, for a complex 3D multibody system, an analytical solution for $\theta^{(T)}$ is not available. We could resort to numerical simulation of the entire airborne phase, in which the character goes through \mathbf{q}_0 , \mathbf{q}^* , and \mathbf{q}_T subsequently. However, involving forward simulation of a full skeleton in the cost function is too costly for our real-time application. Instead, we simulate a simple proxy model with only six DOFs. When the character is holding a pose, the proxy model behaves like a rigid body with a fixed inertia. When the character transitions from one pose to another, we assume the inertia of the proxy model changes linearly within a fixed duration Δt_C ($\Delta t_C = 0.1s$ in our implementation). By simulating the proxy model for the duration of T , we obtain the angle of attack $\theta^{(T)}$ and angular velocity $\omega^{(T)}$ as follows.

$$\begin{aligned} \mathbf{R}(\theta^{(T)}) &= \mathbf{R}(\theta^{(0)}) + \int_{t=0}^{\Delta t_c} [\mathbf{I}_A^{-1}(t)\mathbf{L}] \mathbf{R}(\theta^{(t)}) dt \\ &\quad + \int_{t=\Delta t_c}^{\Delta t_c + \Delta t} [\mathbf{I}^{-1}(\mathbf{q}, \theta^{(t)})\mathbf{L}] \mathbf{R}(\theta^{(t)}) dt \\ &\quad + \int_{t=\Delta t_c + \Delta t}^{2\Delta t_c + \Delta t} [\mathbf{I}_B^{-1}(t)\mathbf{L}] \mathbf{R}(\theta^{(t)}) dt \\ &\quad + \int_{t=2\Delta t_c + \Delta t}^T [\mathbf{I}^{-1}(\mathbf{q}_T, \theta^{(t)})\mathbf{L}] \mathbf{R}(\theta^{(t)}) dt; \end{aligned} \quad (3)$$

$$\omega^{(T)} = \mathbf{I}^{-1}(\mathbf{q}_T, \theta^{(T)})\mathbf{L} \quad (4)$$

where \mathbf{R} is the rotation matrix, $\mathbf{I}(\mathbf{q})$ is an inertia matrix evaluated at pose \mathbf{q} , and \mathbf{L} is the angular momentum. $\mathbf{I}_A(t)$ is an interpolated inertia matrix between $\mathbf{I}(\mathbf{q}_0)$ and $\mathbf{I}(\mathbf{q})$, and similarly, $\mathbf{I}_B(t)$ is an interpolated matrix between $\mathbf{I}(\mathbf{q})$ and $\mathbf{I}(\mathbf{q}_T)$. The operator $[]$ represents the skew symmetric matrix form of a vector.

To formulate an efficient optimization for real-time application, we represent the domain of intermediate pose as a finite set of candidate poses, instead of a continuous high-dimensional Euclidean space. This simplification is justified because a handful of poses is sufficient to effectively change the moment of inertia of the character. As a preprocess step, our algorithm automatically selects the candidate set \mathbf{Q} from a motion capture sequence in which the subject performs range-of-motion exercise. The selection procedure begins with a seed pose $\bar{\mathbf{q}}_0$ and increments the set by adding a new pose $\bar{\mathbf{q}}_{new}$ which maximizes the diversity of inertia (Equation 5). In our experiment, 16 poses are sufficient to present a variety of moment of inertia (Figure 12).

$$\bar{\mathbf{q}}_{new} = \operatorname{argmax}_{\mathbf{q} \in M} \left(\min_{\bar{\mathbf{q}}_j \in Q} \|I(\mathbf{q}) - I(\bar{\mathbf{q}}_j)\| \right) \quad (5)$$

where M contains the poses in the range-of-motion sequence, Q contains the currently selected candidate poses, and $I(\mathbf{q})$ computes the inertia of pose \mathbf{q} .

To find optimal \mathbf{q}^* and Δt^* for each plan, we start from the current pose as \mathbf{q}_0 and loop over each candidate pose in Q . For each candidate pose $\bar{\mathbf{q}}_i$, we search for the best Δt such that $g(\bar{\mathbf{q}}_i, \Delta t)$ is minimized. The search can be done efficiently using one-dimensional Fibonacci algorithm and the proxy-model simulation. The optimal intermediate pose \mathbf{q}^* and its optimal duration Δt^* are used for airborne control.

By design, our algorithm trades off accuracy for efficiency; we use a fast but less accurate proxy-model simulation and a small set of predefined poses. Our algorithm is very efficient so that the character can frequently reassess the situation and replan new poses to correct any errors or adapt to unexpected perturbations.

The frequency of replanning can be determined differently for \mathbf{q}^* and Δt^* . In our

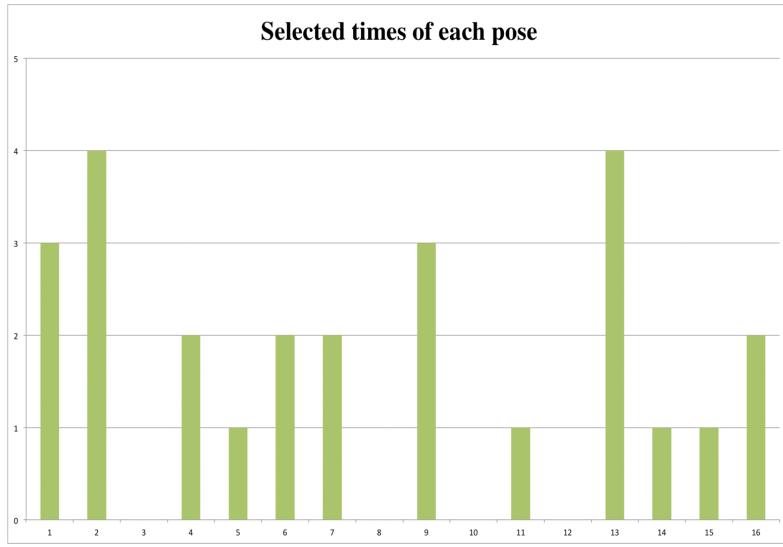
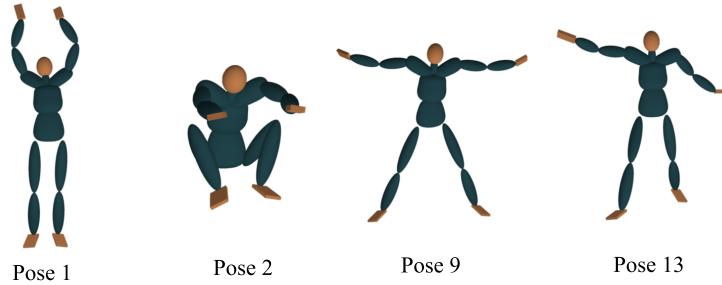


Figure 12: Among 16 poses in \mathbf{Q} , pose 1, 2, 9, and 13 are frequently selected by the airborne controller

implementation, we replan \mathbf{q}^* at a much lower frequency than Δt^* to avoid unnatural frequent change of poses. In addition, we stop replanning when the character is within 0.3 seconds away from the ground.

3.5 Landing Phase

During landing, the character braces for impact, executes rolling action, and gets up on its feet. Although these three stages take very different actions, they share common control goals: modulating the COM and posing important joints. We apply the same control mechanism via *virtual forces* and *PID joint-tracking* to produce the final control forces for the forward simulator (Figure 13).

Virtual forces are effective in controlling the motion of the COM. To achieve a

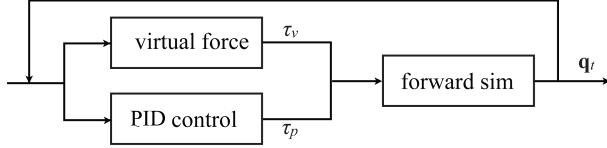


Figure 13: Landing phase controller.

desired acceleration of the COM, $\ddot{\mathbf{c}}$, we compute the virtual force as $\mathbf{f}_v = m\ddot{\mathbf{c}}$ where m is the mass of the character. The equivalent joint torque as if applying \mathbf{f}_v to a point \mathbf{p} on the body is $\tau_v = \mathbf{J}^T(\mathbf{p})\mathbf{f}_v$, where $\mathbf{J}(\mathbf{p})$ is the Jacobian computed at the body point \mathbf{p} . If \mathbf{p} is on a body node in contact with the ground, we apply the opposite force ($\mathbf{f}_v = -m\ddot{\mathbf{c}}$) in order to generate a ground reaction force that pushes the COM in the desired direction. To prevent the character from using excessively large joint torques, we limit the magnitude of the sum of virtual forces. A successful landing motion also requires posing a few important joints at each of the three stages. We track these partial poses with PID servos: $\tau_p = k_p(\bar{q} - q) + k_i \int (\bar{q}_t - q_t)dt - k_v \dot{q}$, where k_p , k_i and k_v are the proportional, integral, and derivative gains respectively, and \bar{q} is the desired joint angle. The final control torque is $\tau_v + \tau_p$. We limit the magnitude of the virtual force to 3000N to prevent excessive usage of joint torques.

3.5.1 Impact Stage

Impact stage is the most critical stage during landing, which requires careful control and execution. Human athletes tend to act like a spring to absorb the effect of impact by flexing their joints between the points of first contact and the COM. Meanwhile, they also utilize friction force from the ground contact to adjust forward linear momentum and angular momentum. Applying these principles, our algorithm utilizes virtual force technique to achieve contact forces for desired momentum. In addition, we use joint tracking to provide sufficient stiffness at contacting limbs and smooth transition to the next stage. If the character chooses the hands-first strategy, the final pose at the end of compression can seamlessly connect to the rolling stage.

With the feet-first strategy, an additional “thrusting” step is required to transition to the rolling stage. We define a “ready-to-roll” pose that guides the character toward a rolling motion (Figure 9, Right). During this additional step, the character tracks the ready-to-roll pose while using its feet to thrust forward after its COM compressed to the lowest point (Figure 14).

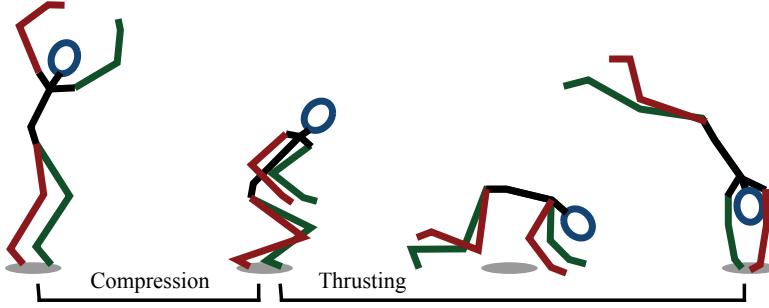


Figure 14: Two-step impact stage for the feet-first strategy.

Virtual force. The most important goal during the impact stage is to stop the downward momentum before the character tragically crashes into the ground. We do so by applying virtual forces to control the vertical position and velocity of the COM. In addition, our algorithm favors virtual forces that result in temporally smooth ground reaction forces to distribute the impact evenly over time. With these control goals, our algorithm aims to use constant acceleration of the COM to achieve the desired COM position \bar{c}_y and velocity $\dot{\bar{c}}_y$ from the current state (c_y and \dot{c}_y).

$$\ddot{c}_y = \frac{1}{2}(\bar{c}_y^2 - \dot{c}_y^2)/(\bar{c}_y - c_y) \quad (6)$$

A virtual force of $-m\ddot{c}_y$ in the vertical direction is then evenly distributed to the end-effectors that are in contact with the ground.

Virtual forces in the horizontal direction are important to achieve the desired forward linear momentum and angular momentum at the end of compression, or to achieve the desired forward thrust for the feet-first strategy. We use a simple feedback mechanism to compute the desired horizontal acceleration of the COM.

$$\ddot{c}_{x/z} = k_v(\bar{c}_{x/z} - \dot{c}_{x/z}) \quad (7)$$

Table 1: Control parameters.

	Hip	Lower spine	Upper spine	Neck	Knee
k_p	90.0	300.0	180.0	10.0	60.0
k_d	20.0	60.0	40.0	2.0	13.0
	Ankle	Clavicle	Shoulder	Elbow	Wrist
k_p	15.0	180.0	120.0	60.0	9.0
k_d	6.0	40.0	27.0	13.5	4.0
\bar{c}_y	\bar{c}_y	$\bar{c}_{x/z}$	k_v	k_p (Eq 8)	ω_{MAX}
0.4m	0.0m/s	4.0m/s	500	800	3.3 Rad/s

where $\bar{c}_{x/z}$ is the desired COM velocity in forward and lateral directions and k_v is the damping coefficient. The corresponding virtual force is distributed to the contacting end-effectors inversely proportional to their distances to the COM.

Joint tracking. In addition to virtual forces, we use PID servos to maintain joint angles of the torso and limbs that are not in contact, while limbs in contact with the ground act like viscous dampers (PID control with a zero spring coefficient). We also use PID control to keep the chin tucked to reduce the chance of the head impacting the ground. Please see Table 1 for all the parameters in our implementation. We set the constant integral gain k_i of contacting limbs as 50, and 0 for all other joints.

3.5.2 Rolling Stage

Once the character’s COM passes the hand-ground contact area with sufficient forward linear and angular momentum, rolling becomes a relatively easy task. As long as the character is holding a pose with a flexed torso, a reasonable rolling motion will readily carry out. If the character wishes to land back on its feet and get up after rolling, it must also maintain forward momentum and lateral balance during the roll.

Virtual force. To this end, we apply a virtual force to guide the horizontal position of the COM toward the feet area, while restricting it above the support polygon formed by contact points. The virtual force is applied on the character’s hands so that it can use the entire upper body to maintain momentum and balance. The virtual force produces the desired acceleration of the COM computed using a

feedback mechanism:

$$\ddot{c}_{x/z} = k_p(\bar{c}_{x/z} - c_{x/z}) \quad (8)$$

where the desired position \bar{c} is set to be the location of the left foot.

Joint tracking. During rolling, the character tracks a simple pose to tuck the head, flex the torso, and position the legs appropriately. We treat legs asymmetrically to both facilitate momentum control and improve the aesthetics of the motion. When the character rolls on its back, it brings the left knee closer to the chest and casually stretches the right leg. This arrangement helps the character to regulate the angular velocity using the right leg while getting ready to stand up on its left foot. Based on the forward angular velocity at the beginning of the rolling stage, we adjust the desired tracking angles for the right knee as:

$$\theta_R = \max((1 - \omega_x/\omega_{MAX})\pi, 0) \quad (9)$$

3.5.3 Getting-Up Stage

The last stage of landing phase is to stand up using the remaining forward momentum. When the COM passes the foot contact, the character will start to elevate its COM to a desired height.

Virtual force. Similar to previous stages, we again apply virtual forces on the feet and the hands to control the vertical and the horizontal positions of the COM respectively. We compute \ddot{c}_y using the same formula from Section 3.5.1 with different desired height of the COM. For $\ddot{c}_{x/z}$, we use the same formula as in Section 3.5.2.

Joint tracking. During the getting-up stage, our algorithm simply tracks the torso and the head to straighten the spine and untuck the chin.



Figure 15: Hands-first landing motion.

3.6 Results

To evaluate the generality of our algorithm, we simulated landing motions with a wide range of initial conditions (Table 2), various landing styles (hands-first, feet-first, consecutive rolls), and different skeleton models. We also demonstrated that our algorithm is robust to unpredicted runtime perturbations and different physical properties of the landing surface. Please see the accompanying video to evaluate the quality of our results.

Table 2: Initial conditions of the examples shown in the video (in order of appearance)

Hands-first landing strategy						
$\vec{C}_y(\text{m})$	$v_x(\text{m/s})$	$v_y(\text{m/s})$	$v_z(\text{m/s})$	$\omega_x(\text{Rad/s})$	$\omega_y(\text{Rad/s})$	$\omega_z(\text{Rad/s})$
10.6	0.0	0.0	4.0	8.7	0.0	0.0
5.8	0.0	0.0	2.3	5.0	0.0	0.0
10.6	0.0	0.0	6.0	2.5	0.0	0.0
2.5	0.0	0.4	8.0	5.0	0.0	0.0
Feet-first landing strategy						
$\vec{C}_y(\text{m})$	$v_x(\text{m/s})$	$v_y(\text{m/s})$	$v_z(\text{m/s})$	$\omega_x(\text{Rad/s})$	$\omega_y(\text{Rad/s})$	$\omega_z(\text{Rad/s})$
6.0	0.0	0.0	5.0	4.0	-1.0	-5.8
2.7	0.0	-1.0	0.0	0.0	0.0	0.0
5.5	1.0	0.0	0.0	0.0	5.0	0.0
9.6	-2.0	0.0	-3.5	0.9	2.1	-3.9

Feet-first landing strategy. The most recommended landing strategy from freerunning community is the feet-first landing. Our results verify that the feet-first landing strategy is indeed very robust for falls with arbitrary linear and angular momentum. There are two key advantages of using feet as the first point of contact. First, average human has longer and stronger legs than arms. Using legs to land provides more time and strength to compress and absorb vertical impact. Second, the feet-first strategy has an additional thrusting step after compression and before rolling stage. During the thrusting step, the character can utilize the contact forces to drastically change the linear and angular velocity in preparation for rolling. Our results show that a successful forward roll can be carried out even when the character is falling with backward and lateral linear velocity or nonplanar angular velocity.

For the feet-first strategy, the coefficients of the landing condition in Equation (1) are: $a = -0.01$, $b = -0.06$, $c = -0.03$, and $d = 0.45$. When the character transitions to the rolling stage, we specified an asymmetric ready-to-roll pose to increase the visual appeal of the motion.

Hands-first landing strategy. Using hands as the first point of contact can generate visually pleasing stunts (Figure 15). For falls with dominant planar velocity (v_z

and ω_x), the hands-first strategy performs as well as the feet-first strategy. However, when the initial condition has large lateral linear momentum or angular momentum in yaw and roll axes, the hands-first strategy becomes less robust. Unlike the feet-first strategy, which has an additional thrusting step, the hands-first strategy is unable to change forward direction drastically after landing. This imposes stringent conditions on the contact forces because, in order to roll successfully, the contact forces must counteract non-planner momentum, while stopping downward momentum and maintaining forward momentum. Such forces usually violate the unilateral constraint of ground reaction force.

For the hands-first strategy, the coefficients of the landing condition are: $a = -0.01$, $b = -0.06$, $c = -0.03$, and $d = 3.08$. Note that the coefficients are identical to those of the feet-first strategy except for the constant term, indicating that the gradient of the angle of attack with respect to the landing velocity is the same between feet-first and hands-first landing strategies.

Consecutive rolls. Once the character starts rolling, it is rather effortless to continue on. By looping the end of the rolling stage back to the beginning, we showed that the character was able to make two consecutive rolls to break a fall with large forward speed. Falling on multiple surfaces is also easy to simulate using our controller. One example demonstrated a continuous sequence of the character landing on the roof of a car, leaping forward, landing again on the sidewalk, and finishing with a dive roll (Figure 7). With our controller, a variety of impressive action sequences can be generated easily without any recorded or pre-scripted motions.

Different skeleton models. The character model we used to generate most examples has a height of 164cm, a weight of 59 kg, and 49 DOFs. The controllers designed for this character can be applied to a drastically different character whose torso is twice as long and twice as wide, comparing to the default character. It also has very

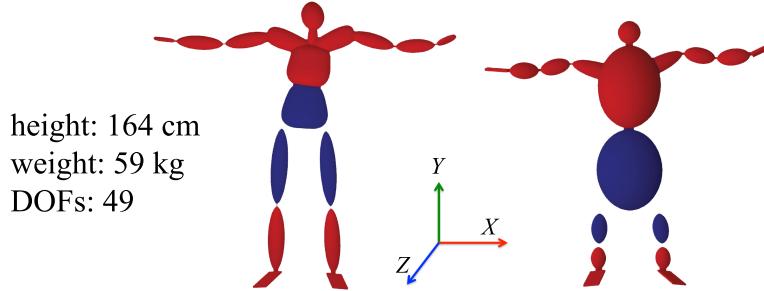


Figure 16: Left: The character model used for most examples. Right: A character with a disproportionately large torso and short legs.

short legs and a small head (Figure 16). We tested both hands-first and feet-first landing strategies on this new character. The results are similar in quality to the default character, although the new character hits its head on the ground because it is difficult to tuck the head with such a short neck. All the control parameters remain the same for the second character, except for \bar{c}_y increasing by $5cm$ and the desired landing angle increasing by $0.25rad$.

Runtime perturbations. One great advantage of physical simulation is that the outcome can be altered on the fly based on user interactions. We demonstrated the interactivity of our simulation in two different ways. First, the user can directly “drag” the character to a different location or orientation when the character is in the air. This example shows off robustness and efficiency of our airborne controller. As the character being relocated, it starts to recalculate and finds a new plan to execute in real-time. Second, we let the user shoot cannons at the character as a source of external forces. When a cannon hits the character, it exerts force and torque on the character, causing a passive response followed by active replanning and execution.

Different landing surfaces. We tested our controller on surfaces with different elasticities and friction coefficients. When the character lands on an elastic surface, such as a gymnastic floor or a trampoline, the character tumbles in the air instead

of rolling on the ground. We generated a continuous sequence where the character stopped the fall on an elastic surface by tumbling three times and finishing with a forward roll. This example shows that various interesting acrobatic sequences can be generated by simply concatenating our falling and rolling controllers repeatedly. In another example, we reduced the friction coefficient to simulate an icy surface. The character was able to use the same control algorithm to roll, but failed to stand up at the end.

3.6.1 Evaluation

Performance. All the results shown in the video were produced on a single core of 3.20GHz CPU. Our program runs at 550 frames per second. The bottleneck of the computation is the optimization routine in the airborne controller. We use Open Dynamic Engine to simulate the character. The time step is set at 0.2 millisecond, and runs the airborne optimization in 50 Hz.

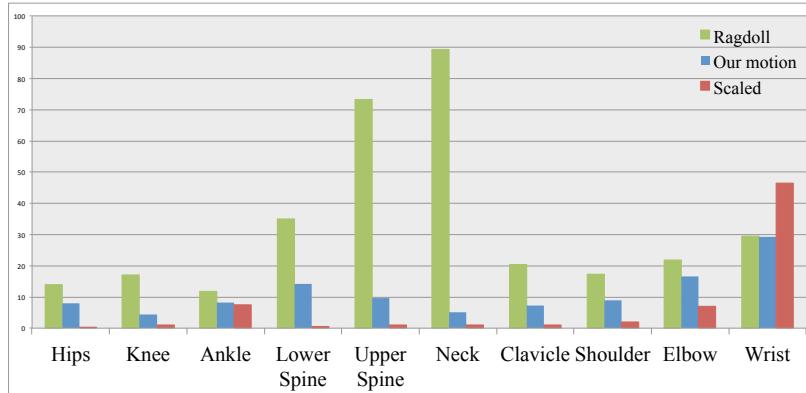


Figure 17: Maximal stress for each joint from a hands-first landing motion. Results are quantitatively similar across all of our simulations. Green: Ragdoll motion. Blue: Our motion. Orange: Joint stress scaled by mass.

Joint stress. We approximated joint stress as the constraint force that holds two rigid bodies together at a joint. For each joint, we computed the maximal joint stress during the landing phase (Figure 17). We observed that, in most trials, the joints

which endure the most impact are those connected to contacting end-effectors (i.e. hands or feet). The spine joints (lumbar and thoracic vertebrae) and hip joints are also subject to large impact. However, when we scaled each joint by the total mass it supports (e.g. the hip joint supports the mass of the entire leg), we found that the joint stress has low variance across the entire character’s body, with the exception of the joints near the end-effectors.

When we compared the joint stress between our motion and a passive ragdoll motion with the same initial condition, the ragdoll motion caused much more damage on the neck and the spine (Figure 17). In fact, the only joints that endured similar amount of stress were those used for the first point of contact (e.g. wrists or ankles). These results validate that our controller indeed produces safer landing motion and protects important body parts. We repeated the experiments for different initial conditions. In the worst case of our experiments, the average joint stress is still four times lower than landing as a passive ragdoll. The data also show that our controller generates less damaging landing motion even when the character cannot roll successfully, such as dropping from 20 meters.

Comparison with video footages. We compared our simulated motion side-by-side with a collection of video footages ([2]). The simulations are based on the same landing strategy and our best guess of the initial conditions from the videos. Although it is not possible to achieve identical motions, results show that our motion is qualitatively similar to the video footages.

3.6.2 Limitations

The main limitation of our work is the lack of balance control after the character stands up. There are many existing balance control algorithms we could implement. However, we chose to defer the implementation until we decide on what the character’s next action should be. In the freerunning scenario, the character transitions

to running motion seamlessly right after a roll. If freerunning is our goal, we would modify the current get-up control algorithm to provide more forward thrust. Other possibilities of the next action include walking, stepping, jumping, or standing still. Different next actions will result in different balance strategies. Ideally, a character should be equipped with motor skills to execute all different balance strategies and autonomously determines which strategy to execute, but this is considered out of the scope of this work.

Another limitation is the predefined landing pose for each landing strategy. This inflexibility can negatively affect the character’s ability to adapt to different environments. For example, if the character lands on a narrow wall, the landing pose needs to be adjusted on the fly. One possible solution is to use a simple inverse kinematics method to compute desired joint angles before landing.



Figure 18: Feet-first landing motion.

3.7 Discussion

We introduced a real-time physics-based technique to simulate strategic falling and landing motions. Our control algorithm reduces joint stress due to landing impact and allows the character to efficiently recover from the fall. Given an arbitrary initial position and velocity in the air, our control algorithm determines an appropriate landing strategy and an optimal sequence of actions to achieve the desired landing velocity and angle of attack. The character utilizes virtual forces and joint-tracking

control mechanisms during the landing phase to successfully turn a fall into a roll. We demonstrated that our control algorithm is general, efficient, and robust by simulating motions from different initial conditions, characters with different body shapes, different physical environments, and scenarios with real-time user perturbations. The algorithm guides the character to land safely without introducing the large stress at every joint except for the contacting end-effectors.

Freerunning is a great exemplar to demonstrate human athletic skills. Those wonderfully simple yet creative movements provide a rich domain for future research directions. Based on the contribution of this work, we would like to explore other highly dynamic skills in freerunning, such as cat crawl, underbar, or turn vault. These motions are extremely interesting and challenging to simulate because they involve sophisticated planning and control in both cognitive and motor control levels, as well as complex interplay between the performer and the environment.

The landing strategies described in this work are suitable for highly dynamic activities, but not optimal for low-clearance falls from standing height. There is a vast body of research work in biomechanics and kinesiology studying fall mechanics of human from standing height. One future direction of interest is to integrate this domain knowledge with physical simulation tools to explore new methods for fall prevention and protection.

APPENDIX A

SOME ANCILLARY STUFF

Ancillary material should be put in appendices, which appear just before the bibliography.

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INDEX

VITA

Perry H. Disdainful was born in an insignificant town whose only claim to fame is that it produced such a fine specimen of a researcher.

Learning Dynamic Motor Skills
for Virtual and Real Humanoids

Sehoon Ha

53 Pages

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