Principle vs Observation: How do people move?



Jehee Lee Movement Research Lab Seoul National University

Principle vs. Observation

Do we have any principles that determine our motion?

Or, do we simply imitate what we have seen before?

What Determines How People Move?

Physics

Mass, inertia, force

Physiology

Muscle, skeleton, tendon

Culture and Psychology

Style, mood



Principles of Motion

Physical laws

Do we need to understand Newton's law for walking?

Optimality principles

Do we optimize for efficiency?

Central pattern generator

Do we have a module that controls a specific motion?

Principles of Motion

Physical laws

Do we need to understand Newton's law for walking? Eg) Physically based simulation

Optimality principles

Do we optimize for efficiency?

Eg) Spacetime optimization

Central pattern generator

Do we have a module that controls a specific motion?

Eg) Controller design

Making Use of Observed Data

Record-and-playback is not enough

Create something new from canned data

Toolbox for animators/programmers

edit, manipulate, segment, splice, blend, and adapt motion capture data.

Motion Capture





The Two Towers | New L

Combine Principle and Observation

Learning principle from observation

Capture symmetry, regularity, and patterns in data

Observation drives principles

Data-driven physics simulation

Principle guides data manipulation

Motion editing using physical properties

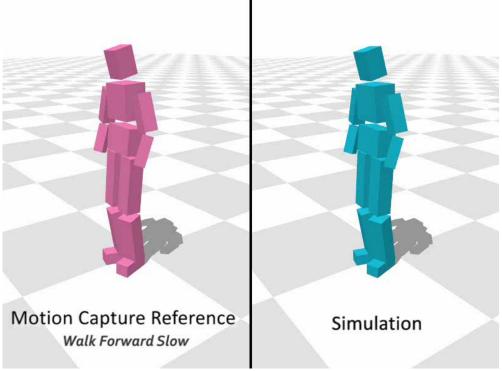
Data-Driven Biped Control

Biped controller is difficult to design

Balance, Robustness
Looks natural, Stylistic gaits



This work was done in collaboration with Yunsang Lee and Sungeun Kim



Goal

Dynamically simulated in real time
As realistic as motion capture data
Equipped with a repertoire of motor skills
Controlled interactively

Motion Data for Controllers

Motion capture is NOT the ground truth

Biped has fewer DOFs

Ideal revolute/ball-and-socket joints

Difficult to estimate body mass/inertia

Sometimes, physically implausible

Simple tracking data would fail

Previous Approaches

Advanced control theory

[Yin 2007] [Tsai 2010] [da Silva 2008] [Muico 2009]

Tracking while compensating error in data

Balance feedback, inverted pendulum, LQR, NQR

Non-linear optimization

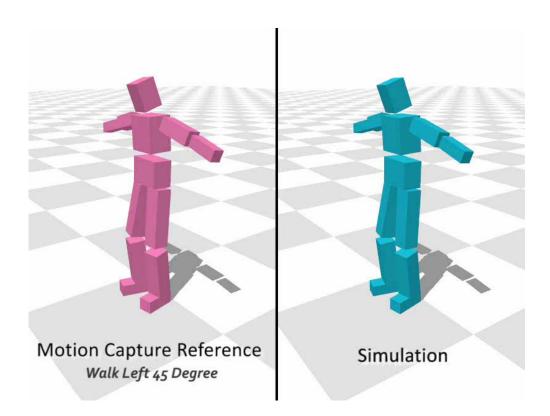
[Sok 2007] [da Silva 2008] [Yin 2008] [Muico 2009] [Wang 2009]

Spacetime optimization for rectifying data

Computationally heavy, cumbersome to implement

Data-driven approach [Sok 2007]

A large collection of motion data Search and regression, statistical modeling



Key Idea

What we use

Simple balance feedback

Continuous modulation of reference trajectory

Synchronization

What we don't use

Model learning, optimization, precomputation

Any animation module can be plugged

Generate stream of reference data on-the-fly

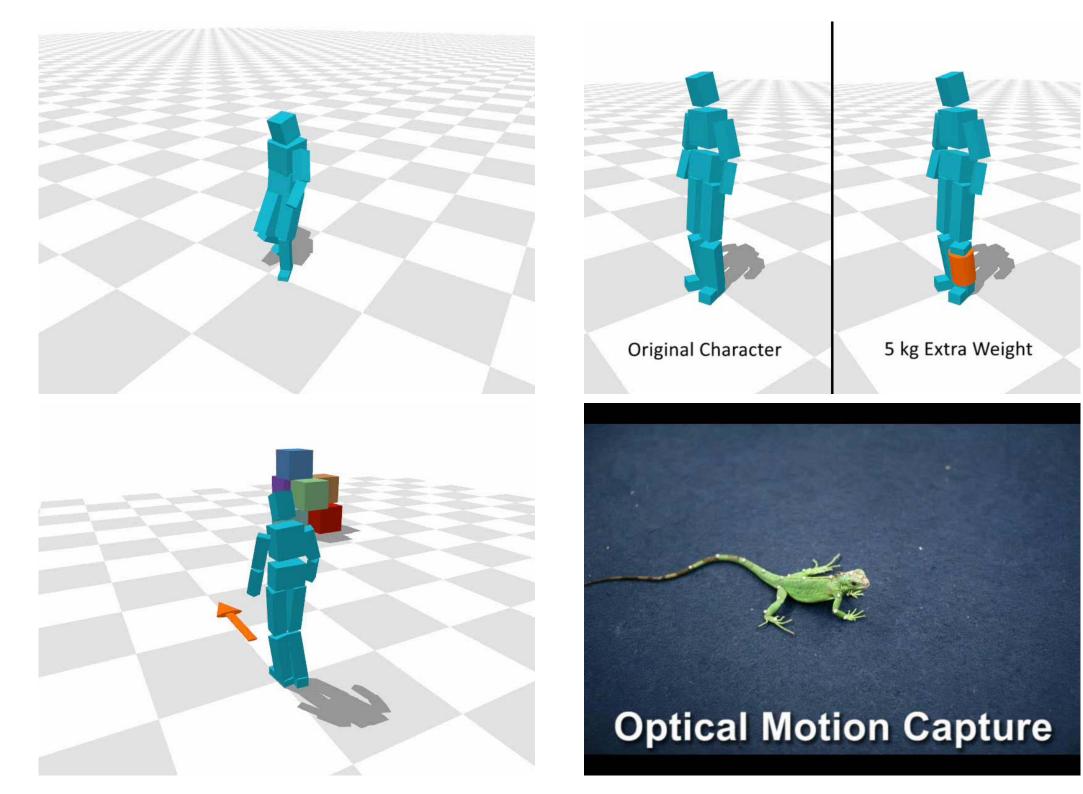
Why is this Simple Approach Work?

Human locomotion is inherently robust

Mimicking what we are doing everyday

Reference trajectory (learned or innate)

A little bit of tweaking



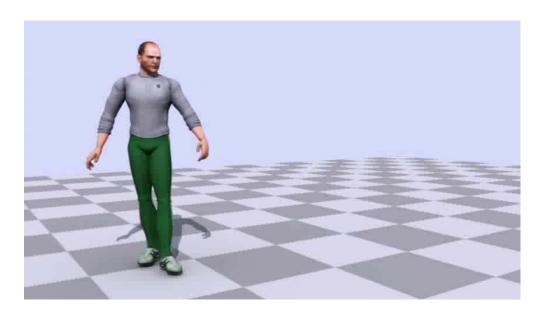


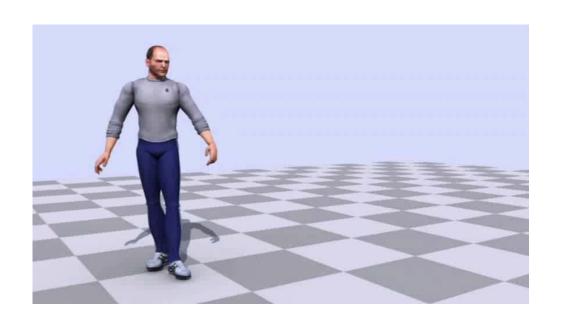


Editing Dynamic Human Motions via Momentum and Force



This work was done in collaboration with Kwang Won Sok, Katsu Yamane, and Jessica Hodgins (SCA 2010)





Manipulating Momentum/Force

Making dull motion more dynamic

Jump higher and wider

Kick harder

Making super heroes from normal persons

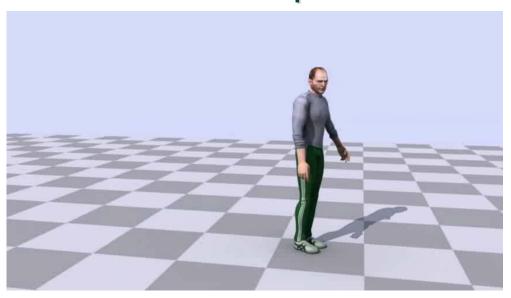
Why is it challenging?

Need to modulate through multiple channels

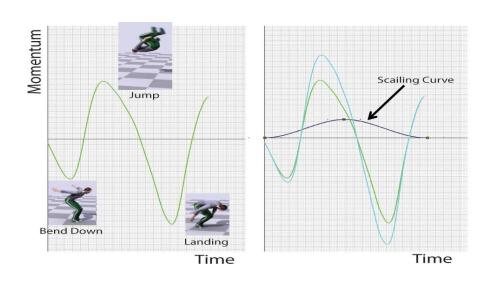
Time, position/orientation, distance

Linear/angular momentum, force/torque

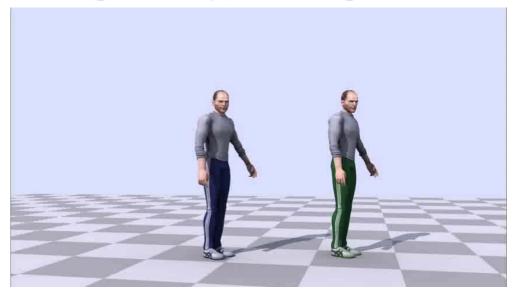
Back Flip



Editing Momentum in Vertical Axis



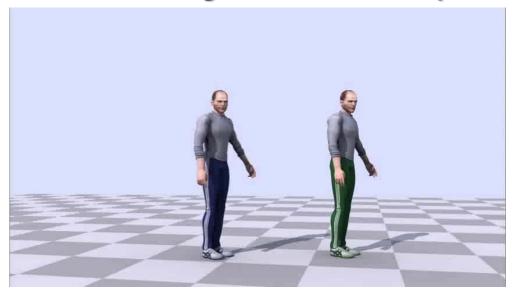
Higher Jump, Fixed Flight Time



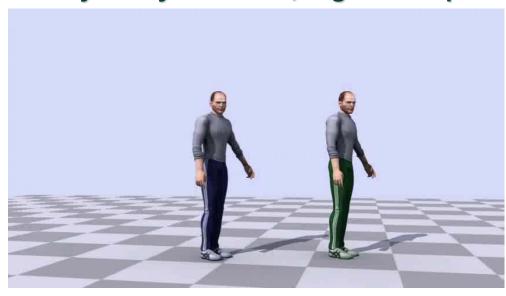
Position Constraint Make Unrealistically Fast Flip



Time Scaling Makes Moon Jump



Physically Plausible, Higher Jump



Reciprocity

Reciprocity

Momentum/Force

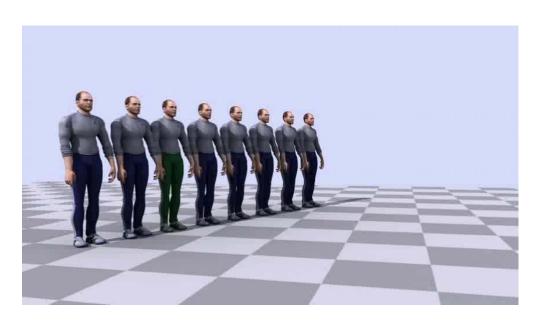
Momentum/Force

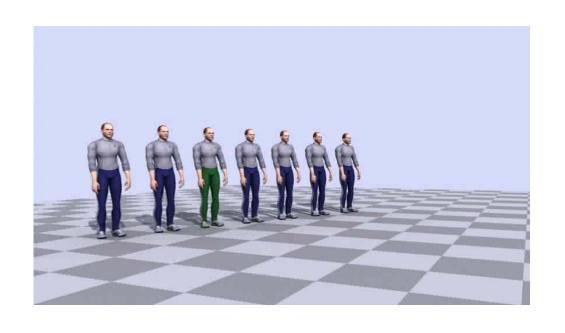
Time Distance

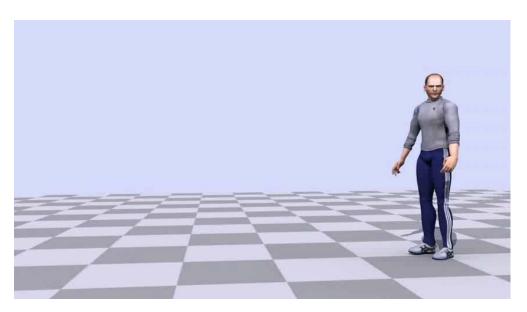
Time
Normalized Dynamics
for Retiming

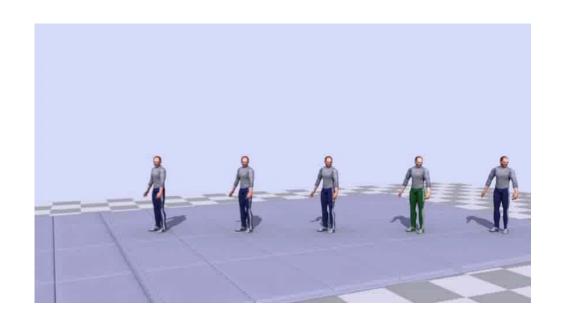
Distance
Dynamic Motion Filter
for Position Constraints



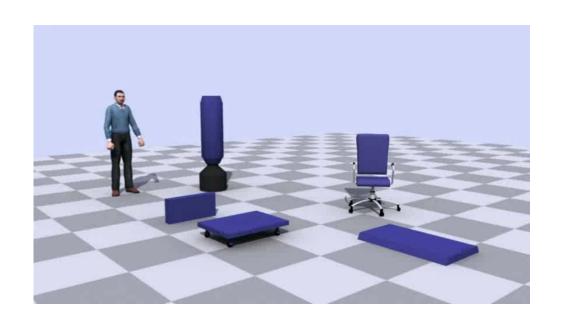


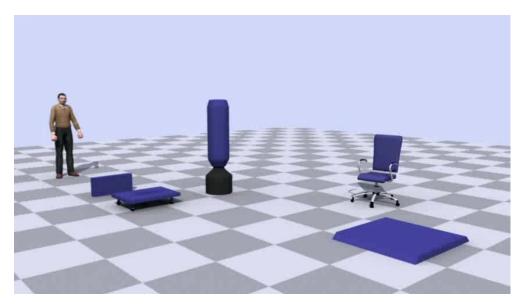












Physical Plausibility

We obey some of physics

Momentum conservation

Consistent with given momentum profiles

Not completely physically correct

Possible violation of friction cone/torque limit
Original motion may not be physically plausible

Data-Driven Crowds

Record real human crowds

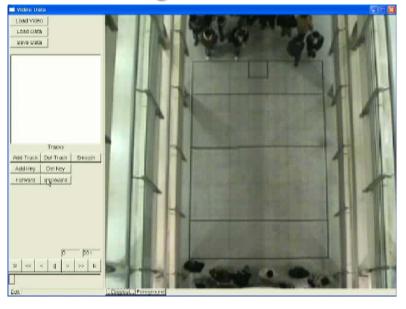
Reproduce their behaviors in virtual crowds

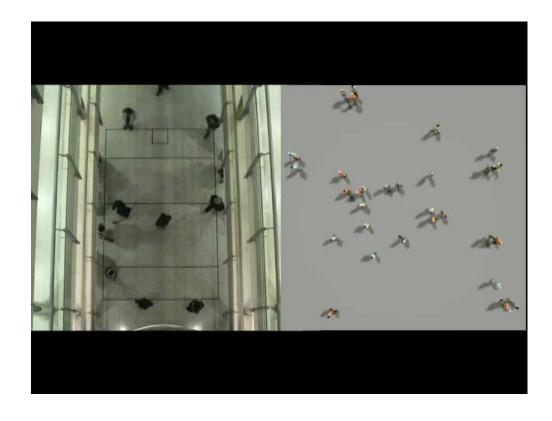
Generalize, manipulate, blend crowd data

This work was done in collaboration with Eunjung Ju, Kang Hoon Lee, Myung Geol Choi, Minji Park, Qyoun Hong, Shigeo Takahashi



Tracking Pedestrians





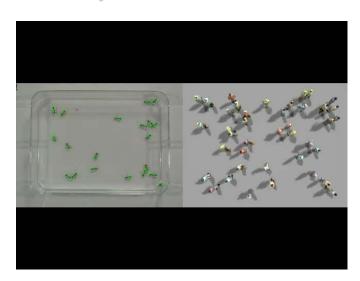
Lining Up



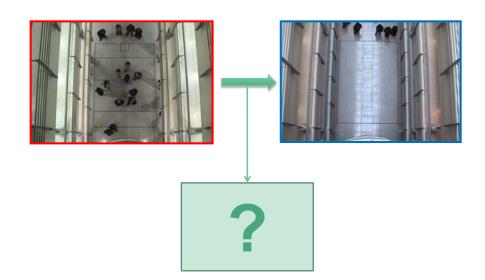
Cluttered Formation



Group Behavior of Ants



Style Transition



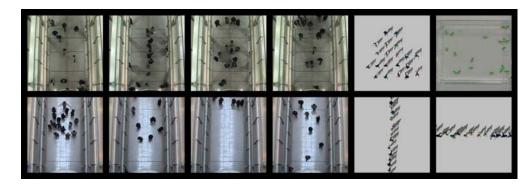
Each Crowd Exhibit Particular "Style"

Density, locomotion styles

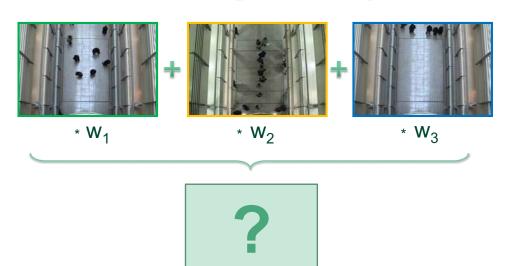
Regularity/persistency of formations

Distribution of individual velocities

Reaction to potential collisions



Interpolating Crowd Styles



Why is it Challenging?

Unstructured formation

Random, regular, clustered

Persistent vs time-varying

Crowds are time-series data

Eg) Aggressive pedestrians try to pass each other

Arbitrary number of agents

No one-to-one correspondence

Morphable Crowds

Interpolate models instead of data

Models should have blendable features

Sampling-based modeling of

high-dimensional neighborhood formation individual trajectory

Data-Driven Crowd Model

Collect state-action pairs from training data

Features include

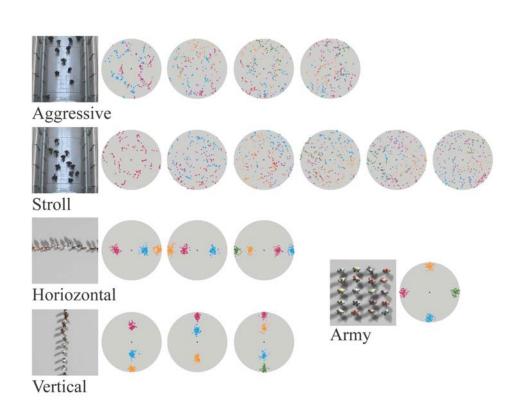
Formation of neighbors

Speed

Intended moving direction

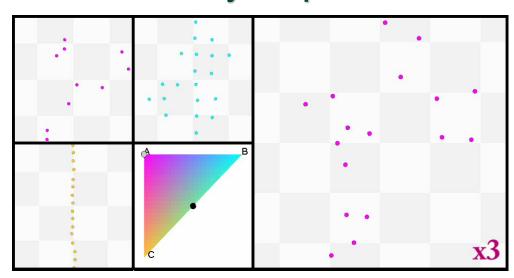
Presence of obstacles

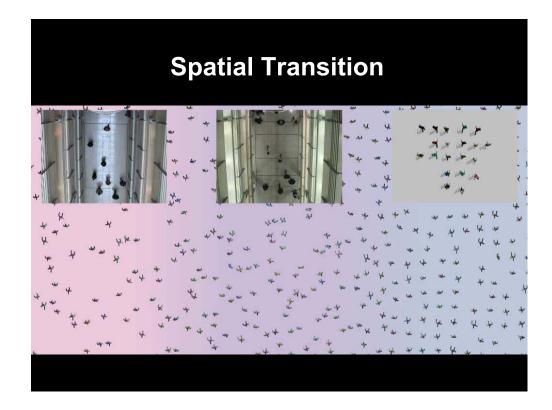
Relative location with respect to environment objects

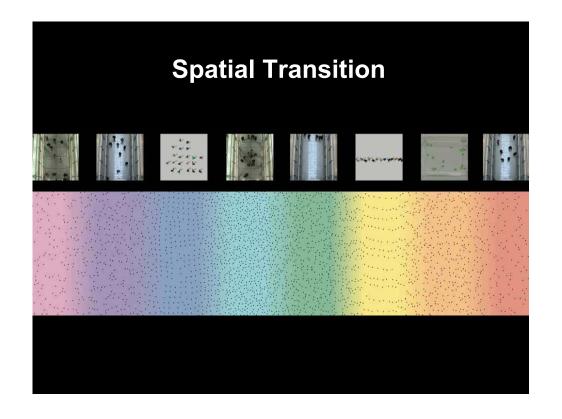


x3March to Chat to March

Three-way Interpolation

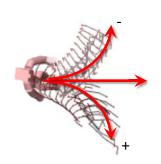


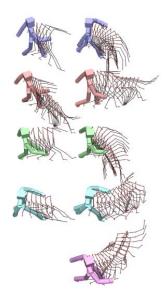




Path Planning with Motion Graphs

- Repertoire of motion choices
- Linear warping to add flexibility
- (Limited horizon) A*-search

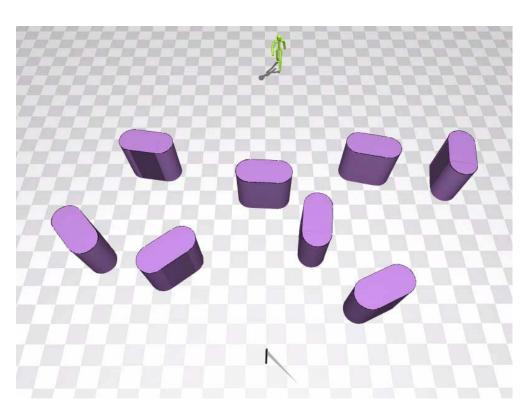


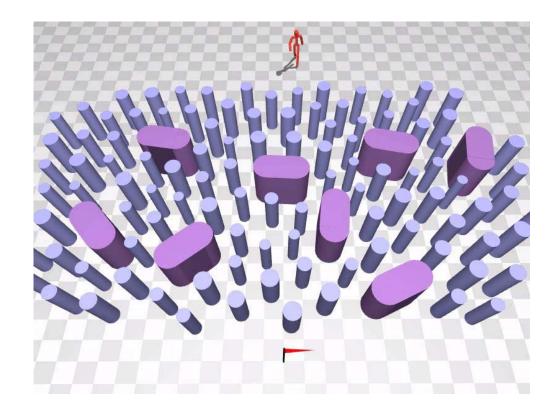


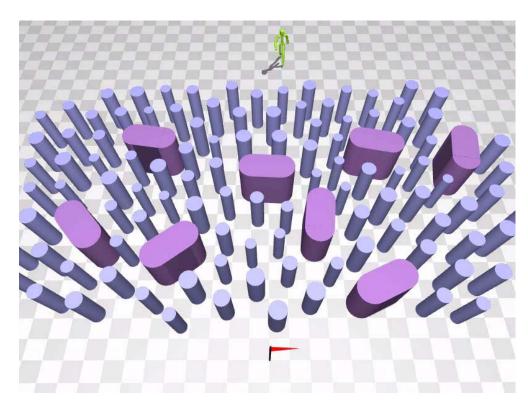
Deformable Motion: Squeezing into Cluttered Environments



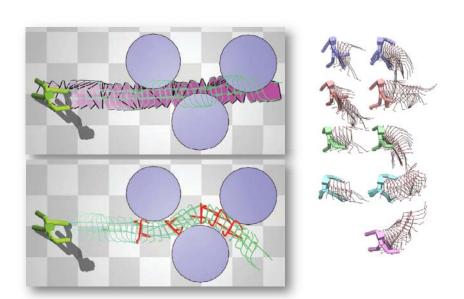
This work was done in collaboration with Myung Geol Choi, Manmyung Kim, Kyung Lyul Hyun



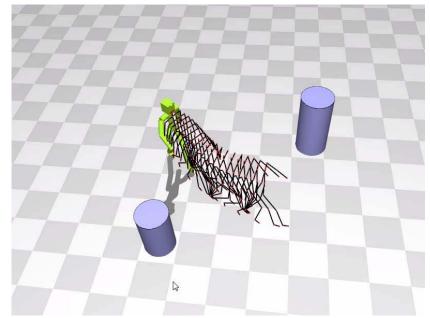




Highly-Constrained Environment

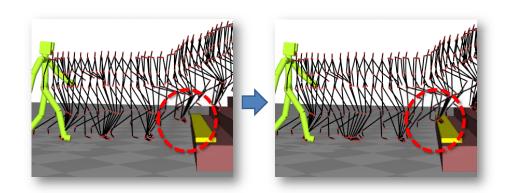


Deformable Motion

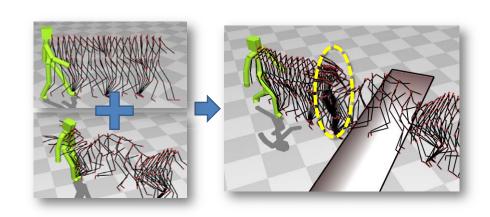


Non-Penetration Constraints

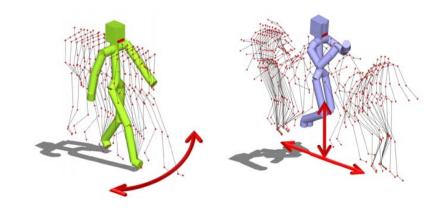
Contact Constraints

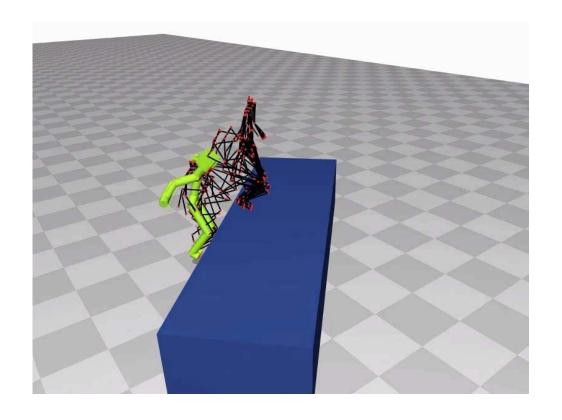


Continuity Constraints

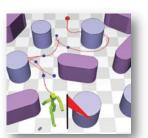


Motion Constraints





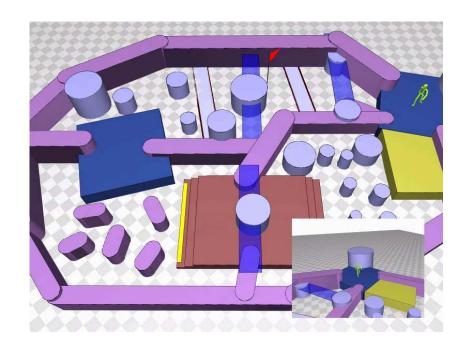
Global Path Planning



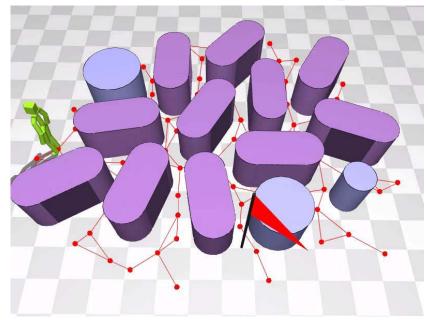
Rapidly-exploring random trees (RRT)



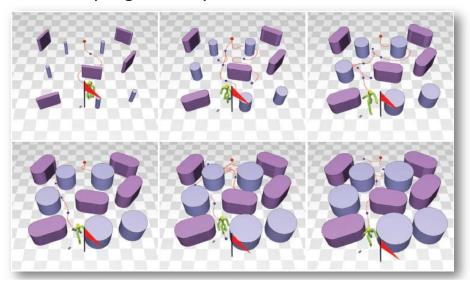
Probabilistic Roadmap (PRM)



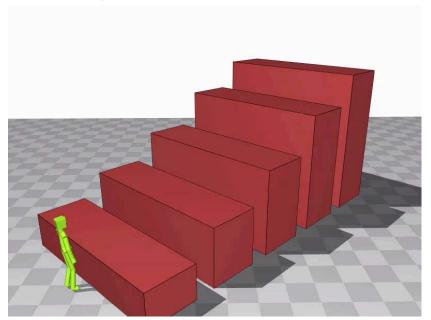
PRM for Narrow Passages



Linear Warping vs. Deformable Motion RRTs for progressively denser environments

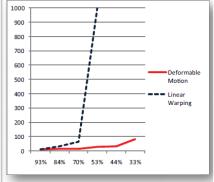


Dynamic Environment



Linear Warping vs. Deformable Motion

e Space	Deformable Motion	Linear Warping
93%	10.71(0.28)	9.43(1.29)
84%	14.00(1.29)	30.43(13.29)
70%	14.57(4.29)	63.86(36.71)
53%	29.00(7.14)	1007.29(803.57)
44%	32.00(10.43)	∞
33%	81.43(43.86)	∞



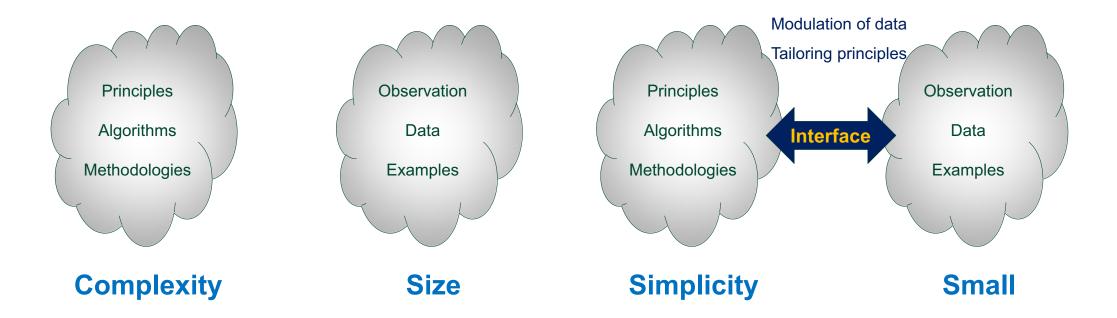
average # of sampling (failure)

Why does it Work?

Known algorithms + motion data

Adding flexibility on data makes big difference Mimicking what we are doing everyday

Powerful local planner for narrow passages



The papers and videos are available at SNU Movement Research Lab

http://mrl.snu.ac.kr



Collaborators

Myung Geol Choi, Kyung Lyul Hyun, Eunjung Ju, Manmyung Kim, Sungeun Kim, Kang Hoon Lee, Yoonsang Lee, Minji Park, Kwang Won Sok, Jessica Hodgins, Shigeo Takahashi, Katsu Yamane