Seminar on Advanced Computer Animation
CSE 888X14

Clone Attack! Perception of Crowd Variety

Rachel McDonnell, Mich´eal Larkin, Simon Dobbyn,
Steven Collins, Carol O'Sullivan
Graphics, Vision and Visualization Group, Trinity College Dublin.
SIGGRAPH 08

Continuation Methods for Adapting Simulated Skills

KangKang Yin, Stelian Coros, Philippe Beaudoin, Michiel van de Panne
University of British Columbia
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Andrew Pamu

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Objective:

To document the perceptual consequences of certain design choices concerning variety in crowds. The results will provide new insights and useful thresholds that will help in creating more realistic, heterogeneous crowds.

Impetus:

- Creating realistic virtual environments with thousands of humans using data driven crowd systems has its limitations
- Factors affecting the perception of variety have not been evaluated till date.

Layout of the experiment:

- Baseline Experiments
- Multiple Clone Experiments

Experimental Setup:

Models:

- 20 different models
- 14 male, 6 female
- 32 unique outfits for each model(hair, skin, clothing and shoes)

Motions:

- 20 different walking gaits (14M,6F) using motion capture

Framework:

- Characters displayed in orthographic matrix format
- Participants were at a distance of 57cm from the screen-largely constant throughout the experiment
- Counting false positives

Baseline Experiments:

Appearance Baseline:

Questions probed:

- Does color variation help in disguising an appearance clone?
- Are some model types more distinctive than others?

Setup:

- 15 naïve participants from different educational backgrounds
- Maximum of 30 seconds to make a choice
- A total of 120(20*2*3) trials for each participant in a random order

Observations:

- Mean reaction time for identification of exact clones was 5.7 seconds, whereas for color modulated clones it was 12.3 seconds.
- It was found that, for the exact clone condition, there was no significant difference between reaction times for any of the models.
- Horizontal pairs were identified most quickly. Vertical pairs were identified second quickest and diagonal pairs took the longest to identify.

Motion Baseline:

Questions probed:

- Are similar motions harder to find than similar appearances?
- Are certain gaits more individual than others?

Setup:

- 9 naïve participants from different educational backgrounds
- Just 6 onscreen characters were used.
- A total of 60(20*3) trials for each participant in a random order

Observations:

- Mean reaction time for this task was 18 seconds
- 3 particular walkers were spotted more easily than the others

Multiple Clone Experiment:

	Appearance (A)	Motion (M)
A_C	varied, some cloned (C)	no motion
$A_C M_C$	varied, some cloned (C)	varied, some cloned (C)
$A_C M_R$	varied, some cloned (C)	random, all different (R)
M_C	all same	varied, some cloned (C)
$M_C A_R$	random, all different (R)	varied, some cloned (C)

Table 1: *A list of the different Multiple Clone experimental conditions.*

Appearance Clones:

- A_C: Appearance Clones
- A_C M_C: Appearance Clones with cloned motion
- A_C M_R: Appearance Clones with random motion

Questions probed:

- Will combining appearance clones with motion clones (*A*C*M*C), so that each appearance clone has the same motion each time, hinder or aid recognition over the case where no motion is present (*A*C)?
- Will random motions applied to appearance clones (*A*C*M*R) make this harder or easier?

Observations:

- models facing in random directions made clones more difficult to spot.
- playing motionsout-of-step made clones more difficult to spot than when they were played in-step.
- random motions made it more difficult to identify clones than when the clones had no motion applied.

Motion Clones:

- M_C: Motion Clones
- M_C A_R: Motion Clones with random appearance

Questions probed:

- Will motion clone matching at different levels of multiplicity be a much harder task than appearance clone matching?
- Will motion clones be disguised when appearance is varied?

Observations:

- The average reaction time for motion clones was far slower than for appearance
- clones (28 seconds).
- Surprisingly, motion clones were not disguised
- when appearance varied

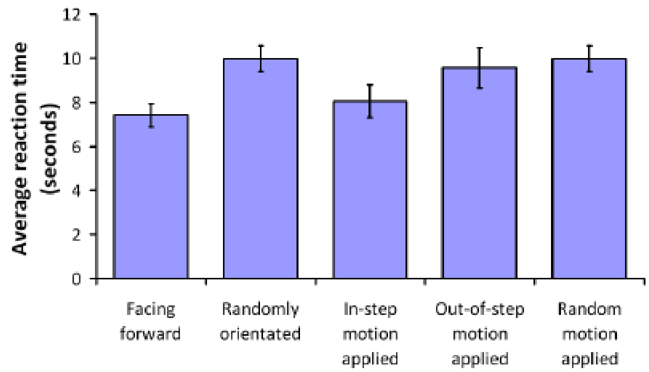


Figure 8: *Appearance Clone effects: Reaction times averaged over the 10 number of clone levels.*

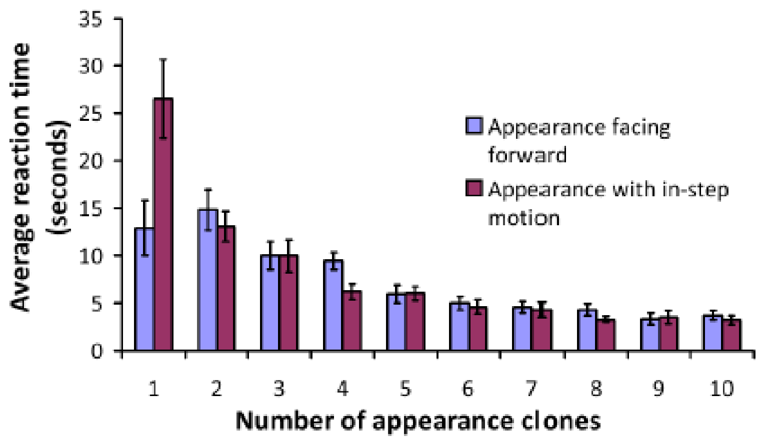


Figure 9: *Interaction between number of clones and the presence or absence of motion.*

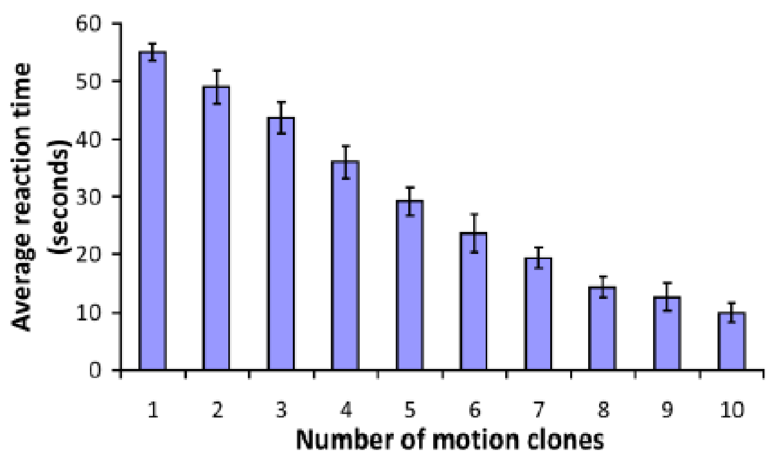


Figure 12: *Main effect of number of motion clones in the Motion Clone Detection Experiment.*

Conclusion and summary of results:

- Appearance clones were easier to detect than motion clones
- Increasing clone multiplicity reduced variety significantly
- No appearance model was more easily detected than others
- Certain gaits were more distinctive than others
- Color modulation and spatial separation effectively masked appearance clones
- Combined appearance/motion clones were only harder to find than static appearance clones when their cloned motions were
- out-of-step
- Appearance clones were also harder to find when combined with random motions
- Motion clones were not affected at all by appearance, even with random appearances

Exposure	# Appearance clones	# Motion Clones
5 seconds	8	10
10 seconds	4	10
15 seconds	2	9
20 seconds	none	7

Table 2: *Summary of thresholds.*

Continuation Methods for Adapting Simulated Skills

KangKang Yin, Stelian Coros, Philippe Beaudoin, Michiel van de Panne

University of British Columbia

SIGGRAPH 08

Objective:

To come up with techniques for generalizing a controller for physics-based walking to significantly different tasks, such as climbing a large step up, or pushing a heavy object. The paper describes and evaluates a number of choices in applying continuation methods to adapting walking gaits for tasks involving interaction with the environment.

Impetus:

- Animated characters should exhibit rich and purposeful behavior if they are to mimic human abilities.
- Data-driven approaches are a solution that come at a price-highly resource intensive.

What is the idea of continuation methods?

Questions addressed:

- How quickly should the continuation be advanced, i.e., what should the step height increment be?
- Are gradient-descent techniques sufficient to make the required adaptations?
- For any given step height, what objective function should drive the adaptation?

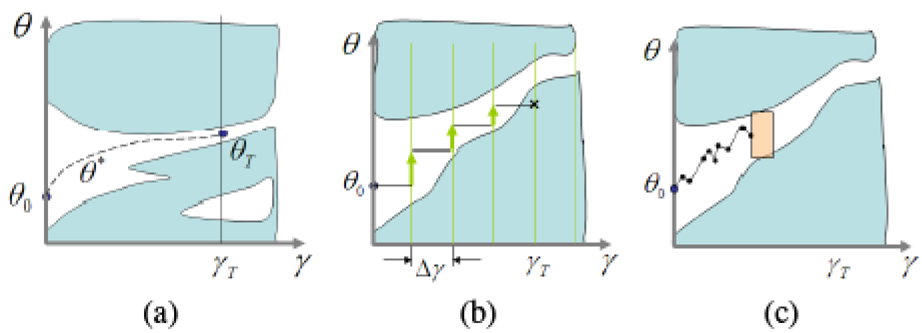


Figure 2: *(a) Abstract view of the continuation problem. The shaded regions denote failure regions where no meaningful gradient can be computed. γ is an environment-based continuation parameter. θ is the vector of free control parameters. (b) Gradient descent with fixed-step continuation (GRAD). (c) Stochastic local search continuation (STOC).*

- A central issue is deciding how style optimization and continuation advancement should be coupled. The paper investigates gradient-descent, local-stochastic search, and hybrid continuation methods, each of which offer a different degree of coupling between the two problem features.
- The methods must satisfy the multiple goals of advancing the continuation process, staying out of failure regions, and optimizing stylistic aspects of the motion.

Continuation methods:
GRAD:

- Advancement of continuation with a fixed step-size
- Gradient descent is used to optimize the style of motion
- Tracks the optimal style θ* in a systematic fashion
- Gradients are expensive to compute, local minima are possible
- Solution can easily be led into a failure region

HYBRID

- Builds on the GRAD method with a couple of changes
- First change:

$$\tilde{\theta}_{i+1} = \theta_i + (\gamma_{i+1} - \gamma_i)(\theta_i - \theta_{i-1})/(\gamma_i - \gamma_{i-1})$$

- Second change:

Allow for adaptation to the continuation step-regular sampling is done in a trust region fro linear prediction

Trust region: $\delta\gamma \in [0.2\Delta\gamma, 2\Delta\gamma]$

STOC1,STOC2,STOC3:

- STOC1, STOC2, and STOC3 reward continuation to different degrees, given by c_γ = c0, c_γ = 10c0, and c_γ = 100c0, respectively

$$f(\theta) = g(\theta) + w_\theta \delta\theta^T W \delta\theta + c_\gamma \gamma.$$

- At any given step, the search is advanced by drawing sample points in a uniform random fashion from a given window around the current solution:

$$(\gamma \in [\gamma_i, \gamma_i + \Delta\gamma/2],\ \theta \in [\theta_i - \Delta\theta, \theta_i + \Delta\theta])$$

- Search proceeds in a greedy fashion
- Avoids failure regions and local minima in windowed sample regions

Problem Representation:

- The default controller is an implementation of the four-state finite state machine (FSM) walk controller
- Each of the states specifies target angles for all the joints, which are used by PD-controllers in order to compute applied joint torques.
- All states have a dwell-time in our implementation, including those based on foot contacts

$$f(\theta) = g(\theta) + w_{\theta}\delta\theta^{T} W \delta\theta + c_{\gamma}\gamma.$$

- First term rewards a desired motion style
- The second term penalizes making large changes to the original control parameters. W is a diagonal weighting matrix (we use W = I)
- The optional third term rewards advancing the continuation in the case of STOC1, STOC2, and STOC3.

STEPUP:

- One complete gait cycle i.e a right step followed by a left step constitutes four states and each state has 10 parameters –a total of 40 parameters
- The per-state parameters encompass the sagittal-plane target angles for the left-and-right ankles, left-and-right knees, the swing hip, and the waist. Four

additional parameters are given by cd (lateral and sagittal), the lateral swing-hip angle, and the state dwell-time.

$$g(\theta) = \sum_{i=0}^{1} (||\hat{l}_i - l_i||^2 + ||\hat{h}_i - h_i||^2 + w_1 * c_i) + w_2 * \sum_{i=2}^{5} (||\hat{l}_i - l_i||^2)$$

where i is a step index, $\hat{l}_i$ is a desired step length, l_i is the actual step length, $\hat{h}_i$ is the desired height of the swing foot center-of-mass when it passes the edge of the step, h_i is the corresponding actual height, c_i is the time integral, in seconds, of the combined unwanted contact durations of the swing foot with the environment, and w1 and w2 are constants. We use $\hat{h}_i$ = g +0.2m, w1 = 10, w2 = 0.1, and $\hat{l}_i$ = (0.4,0.1,0.2,0.2,0.2,0.2).

STEPOVER :
The choices of optimization parameters, optimization FSM states, and other parameters are the same as for STEPUP. The style term of the objective function is the same as that used for STEPUP.

PUSH:

- The density of the object is the continuation variable
- $\Delta\gamma = 3.0 kg/m^3$, $V = 0.72 m^3$
- $\mu = 0.8$

- Only two modifiable states because of the left-right symmetry-16 dimensional parameter space

$$g(\theta) = \sum_{i=2}^{7} (||\hat{l} - l_i||^2)$$

HILL:

- Slope of the incline is the continuation variable
- Δγ=3 degrees
- The modifiable parameters consist of the target sagittal angles for the left-and-right ankles, the left-and-right knees, swing hip, and waist, giving six parameters per state. As for the PUSH task, there are only two modifiable states because of left-right symmetry, yielding a 12-dimensional parameter vector.

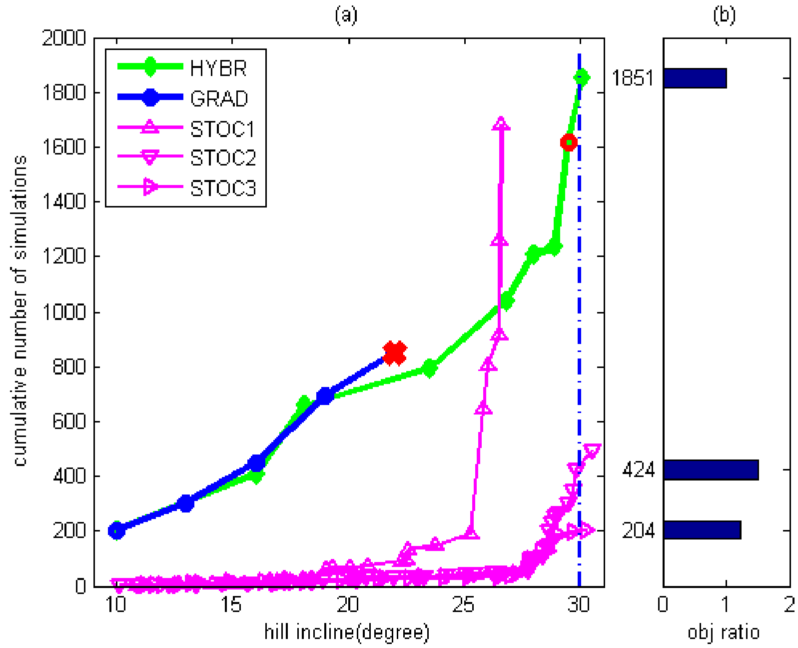
ICE:

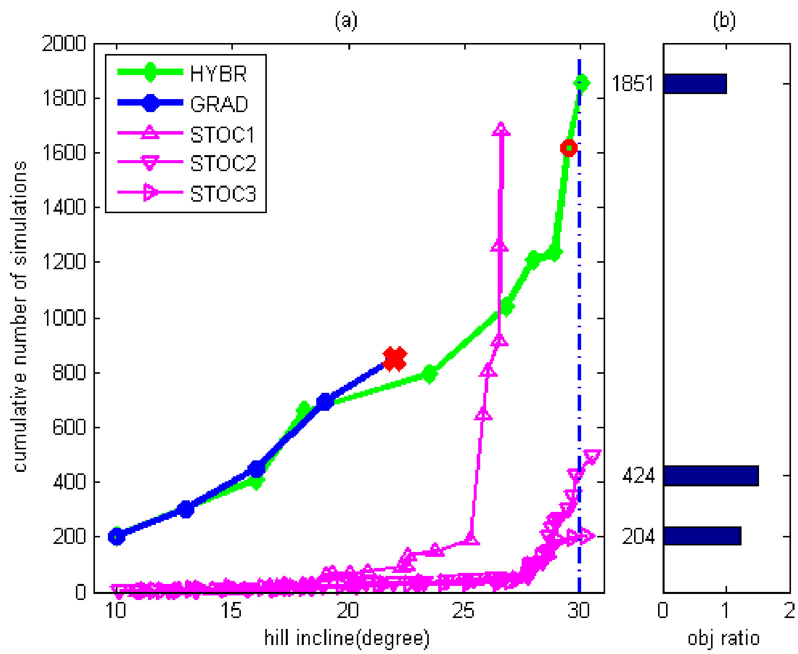
- The coefficient of friction is the continuation variable
- μ = 0.18, which is the lowest friction supported by the initial walking gait.
- Δ μ = −0.03.

$$g(\theta) = \sum_{i=2}^{7} (||\hat{l} - l_i||^2 + s_i^2)$$

- where ˆl = 0.2m and si is the foot-slippage, measured as the movement in the ground plane of the center of mass of the stance foot.

Results:


(a)
(b)
HYBR
GRAD
STOC1
STOC2
STOC3
cumulative number of simulations
hill incline(degree)
obj ratio
1851
424
204


(a)
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HYBR
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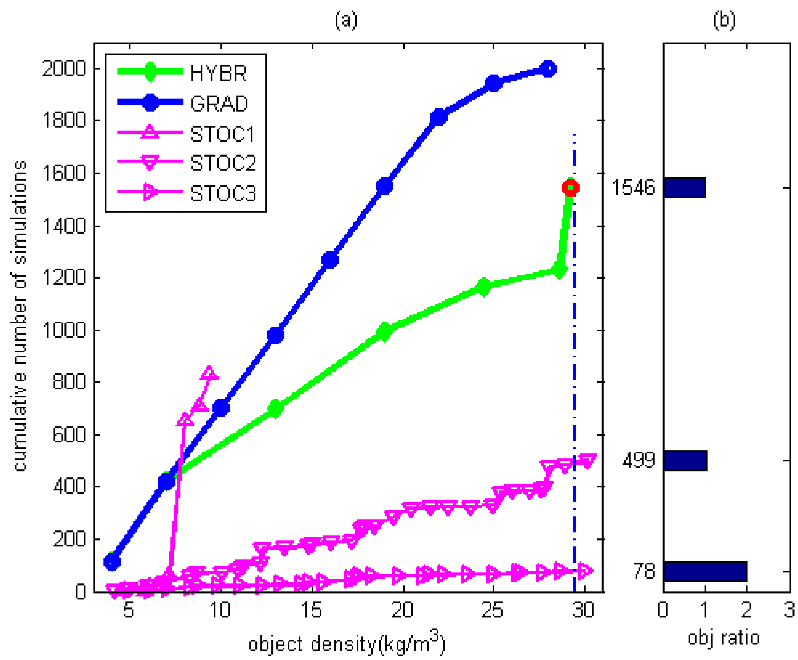
1851
424
204


(a)
(b)
HYBR
GRAD
STOC1
STOC2
STOC3
cumulative number of simulations
object density(kg/m3)
obj ratio
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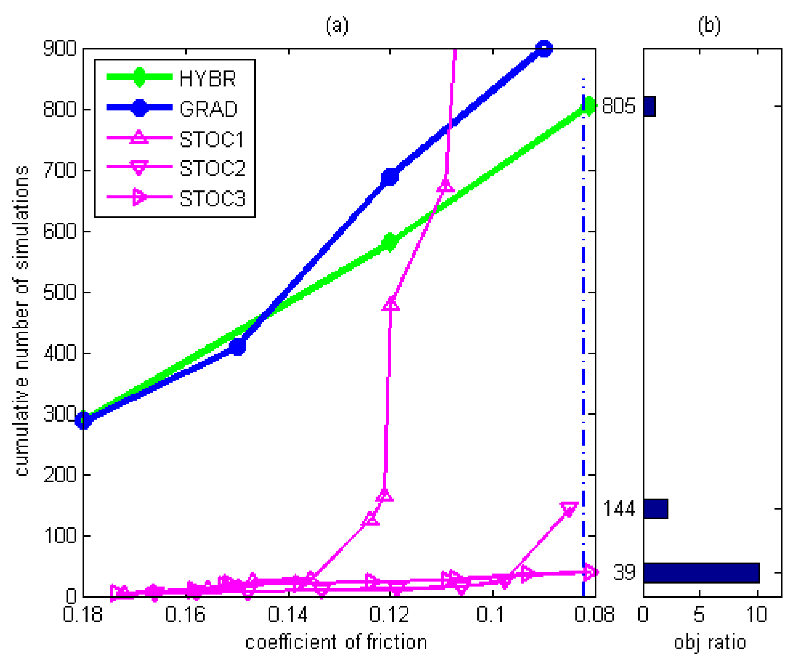
499
78
0 200 400 600 800 1000 1200 1400 1600 1800 2000
5 10 15 20 25 30
0 1 2 3


(a)
(b)
HYBR
GRAD
STOC1
STOC2
STOC3
cumulative number of simulations
coefficient of friction
obj ratio
805
144
39
0 100 200 300 400 500 600 700 800 900
0.18 0.16 0.14 0.12 0.1 0.08
0 5 10