Adaptation of Surrogate Tasks for Bipedal Walk Optimization

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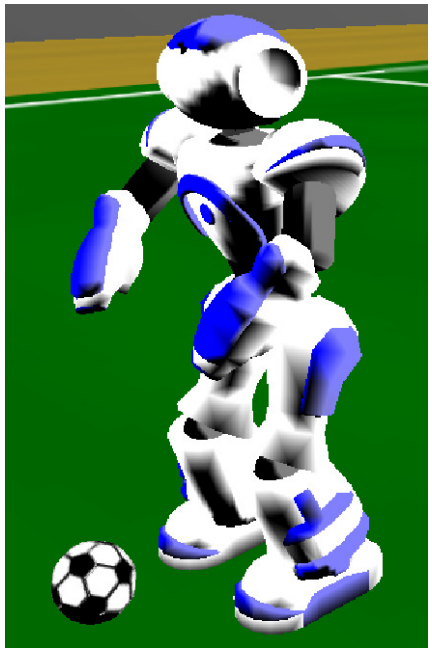
Outline

- Bipedal walk optimization problem
- Overview of RoboCup
- Surrogate optimization task
- Adaptation of surrogate optimization task
- Initial results
- Ongoing/future work

RoboCup 3D Simulation Domain

- Teams of 11 vs 11 autonomous robots play soccer
- Realistic physics using Open Dynamics Engine (ODE)
- Simulated robots modeled after Aldebaran Nao robot
- Robot receives noisy visual information about environment
- Robots can communicate with each other over limited bandwidth channel



Initial Walk Parameters

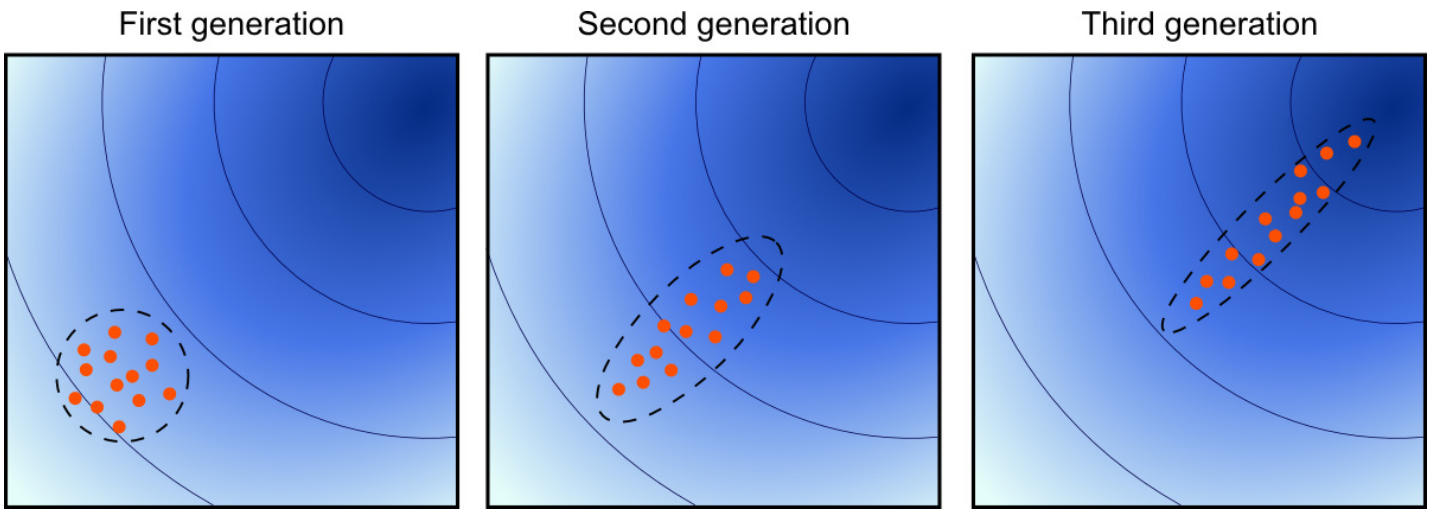
- Designed and hand-tuned to work on the actual Nao robot
- Provides a slow and stable walk

Video

Omnidirectional Walk Engine Parameters to Optimize

Notation	Description
$\text{maxStep}_{\{x,y,\theta\}}$	Maximum step sizes allowed for x, y, and θ
y_{shift}	Side to side shift amount with no side velocity
z_{torso}	Height of the torso from the ground
z_{step}	Maximum height of the foot from the ground
f_{g}	Fraction of a phase that the swing foot spends on the ground before lifting
f_{a}	Fraction that the swing foot spends in the air
f_{s}	Fraction before the swing foot starts moving
f_{m}	Fraction that the swing foot spends moving
ϕ_{length}	Duration of a single step
δ_{step}	Factor of how fast the step sizes change
x_{offset}	Constant offset between the torso and feet
x_{factor}	Factor of the step size applied to the forwards position of the torso
$\delta_{\text{target\{tilt,roll\}}}$	Factors of how fast tilt and roll adjusts occur for balance control
$\text{ankle}_{\text{offset}}$	Angle offset of the swing leg foot to prevent landing on toe
err_{norm}	Maximum COM error before the steps are slowed
err_{max}	Maximum COM error before all velocity reach 0
$\text{COM}_{\text{offset}}$	Default COM forward offset
$\delta_{\text{COM}\{x,y,\theta\}}$	Factors of how fast the COM changes x, y, and θ values for reactive balance control
$\delta_{\text{arm}\{x,y\}}$	Factors of how fast the arm x and y offsets change for balance control

CMA-ES (Covariance Matrix Adaptation Evolutionary Strategy)



(image from wikipedia)

- Evolutionary numerical optimization method
- Candidates sampled from multidimensional Gaussian and evaluated for their fitness
- Weighted average of members with highest fitness used to update mean of distribution
- Covariance update using evolution paths controls search step sizes

SoccerPlaying Optimization Task

- Teams play a 5 minute game against each other
- Less than 5 minutes produces poor results
- Want to find a faster surrogate task to use for optimization

$$\text{Fitness} = \textit{goalsDifferential} * 15\{\frac{1}{2}\text{Field\_Length}\} + \textit{avgBallPosition}$$

Video

What is RoboCup?

- International robotics competition founded in 1997
- Consists of many different autonomous robot soccer leagues
- Includes non-soccer robot competitions: RoboCup Rescue & RoboCup @Home



RoboCup Goal

Have a team of fully autonomous humanoid robot soccer players beat the human World Cup champions by 2050

Humans vs Robots

Obstacle Course Surrogate Walk Optimization Task

- Playing soccer games takes 5 minutes while obstacle course takes 30 seconds
- Agent is measured on its cummulative performance across 11 activities
- Agent given reward for distance it is able to move toward active targets
- Agent is penalized it if falls over

Optimized Walk in Action

Final championship match at RoboCup 2011

What surrogate optimization task to use for optimizing a walk?

Obstacle course activities developed from watching 100s of simulated soccer games

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What surrogate optimization task to use for optimizing a walk?

- Experimented with different activities for an obstacle course
  - Infant walk trajectories
  - Record walk trajectories from gameplay

Obstacle course activities developed from watching 100s of simulated soccer games

What surrogate optimization task to use for optimizing a walk?

- Experimented with different activities for an obstacle course
  - Infant walk trajectories
  - Record walk trajectories from gameplay

- Automate the construction of surrogate walking task activities by learning/evolving activities during the course of optimization

Obstacle course activities developed from watching 100s of simulated soccer games

ObstacleCourse Surrogate Task Representation

```
WAYPOINT duration XCoordinate YCoordinate
STOP duration
. . .
. . .
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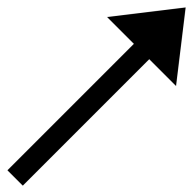
$$\text{reward}_{\text{WAYPOINT}} = d_{\text{target}} \frac{t_{\text{total}}}{t_{\text{taken}}} - \mathit{Fall}$$

$$\text{reward}_{\text{STOP}} = -d_{\text{moved}} - \mathit{Fall}$$

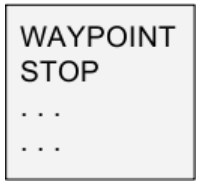
- Series of WAYPOINT and STOP targets



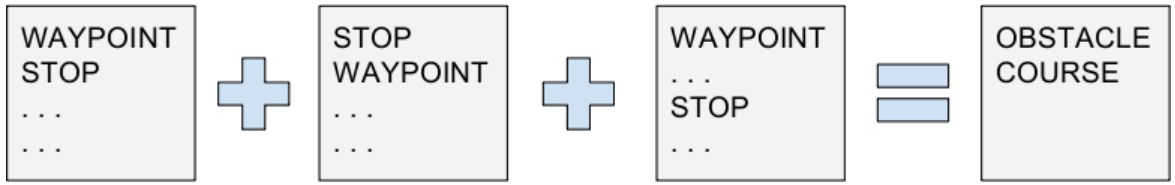
- Agent rewarded for distance traveled for WAYPOINTS, penalized for any movement during STOP targets, and penalized if the robot falls

ObstacleCourse Surrogate Task Genetic Algorithm

- ObstacleCourse basis subtasks are series of WAYPOINT and STOP targets fixed to be a set duration of time



- Modify ObstacleCourse basis subtasks that are concatenated together to form ObstacleCourse surrogate task

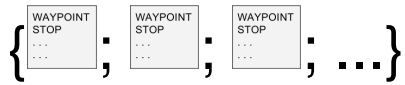


- Given K ObstacleCourse subtasks generate additional K new ObstacleCourse basis subtasks
  - Generate K/2 new ObstacleCourse subtasks through crossover
  - Generate K/2 new ObstacleCourse subtasks through mutation
  - Normalize new ObstacleCourse subtasks so that sum of target durations is fixed duration

Adapting Surrogate Walk Optimization Task

- Every nth generation of CMA-ES
  - Evaluate CMA-ES population on SoccerPlaying task

  - Generate set of new ObstacleCourse basis subtasks using GA

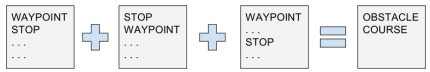


  - Evaluate all member of CMA-ES population on each ObstacleCourse basis subtask (both pre-existing and new)

  - Rank ObstacleCourse subtasks based on Spearman's rank correlation with SoccerPlaying task

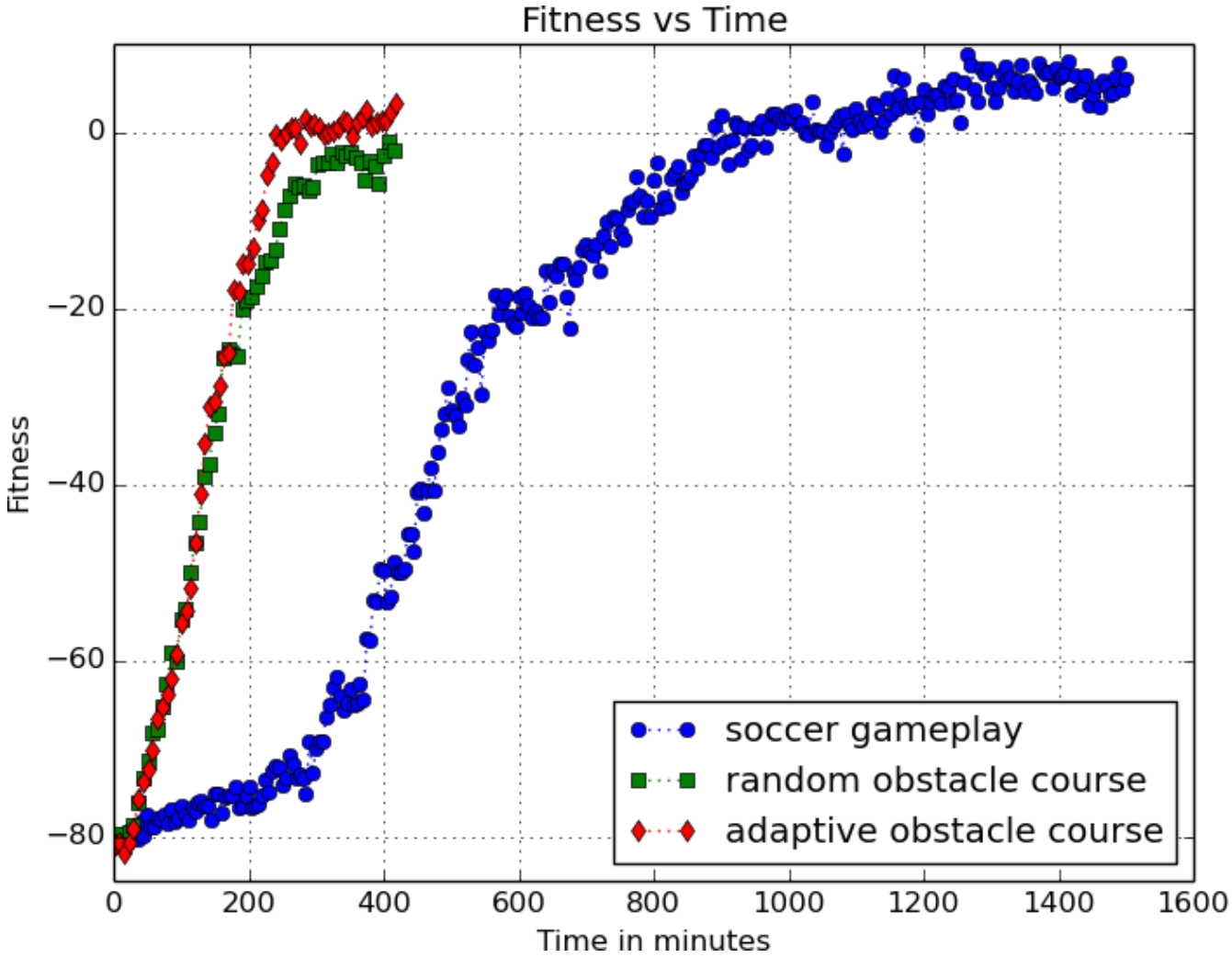
1. 2. 3. ...

  - Choose top half of ObstacleCourse substasks to use as ObstacleCourse surrogate task



- All other generations of CMA-ES
  - Evaluate all members of CMA-ES population on current ObstacleCourse surrogate task

Initial Results



- All optimizations run across 300 gens of CMA-ES pop 150
- Obstacle course data points were each averaged across 3 independent optimization runs

In Progress Work: Co-dependence of Basis Subtasks

- Take into account co-dependence of tasks
- Currently GA can converge on a single highly correlated ObstacleCourse basis subtask
- Want to find set of basis subtasks that is highly correlated with SoccerPlaying task
- Rank by inverse of Spearman's rank correlation to SoccerPlaying task all sets of every basis subtasks with one left out

Future Work: Information Gain for Selection of Basis Subtasks

$$\texttt{InfoGain}(\mathit{fitness}, \mathit{task}) = H(\mathit{fitness}) - \sum_{v \in \mathit{values}(\mathit{task})} \left(\frac{|\{x \in \mathit{fitness} | \mathit{value}(x, \mathit{task}) = v\}|}{|\mathit{fitness}|} \cdot H(\{x \in \mathit{fitness} | \mathit{value}(x, \mathit{task}) = v\}) \right)$$

- Use information gain instead of Spearman's rank correlation
- Measures reduction of uncertainty (KL divergence)
- More general and can measure non-monotonic relationships

Future Work: PCA Selection of Basis Subtasks

- Perform PCA on basis subtask rewards matrix
- Pick top principal components (explaining most observed variance)
- Compute correlation of top principal components with SoccerPlaying task fitness
- Choose ObstacleCourse basis subtasks based on principal component coefficents with highest correlated principal components

Future Work: Improvements to Estimation of True Fitness from Surrogate Subtasks

- Use regression to map rewards from ObstacleCourse basis subtasks to SoccerPlaying task fitness
- Basically weighting the importance/contribution of each subtask to estimate of SoccerPlaying task fitness
- Regularized non-negative least squared regression
- Gaussian process regression and locally weighted regression

Related Work

- Reweighting tasks: P. MacAlpine, E. Liebman, and P. Stone. Simultaneous learning and reshaping of an approximated optimization task, 2013.
- Survey paper: Y. Jin. Surrogate-assisted evolutionary computation: Recent advances and future challenges, 2011.
- ACM-ES: I. Loshchilov, M. Schoenauer, and M. Sebag. Comparison-based optimizers need comparison-based surrogates, 2010.
- ^{s*}ACM-ES: I. Loshchilov, M. Schoenauer, and M. Sebag. Self-adaptive surrogate-assisted covariance matrix adaptation evolution strategy, 2012.

More Information

UT Austin Villa 3D Simulation Team homepage:
www.cs.utexas.edu/~AustinVilla/sim/3dsimulation/

Email: patmac@cs.utexas.edu

Video

RoboCup 2015 Highlights