Learning Robot Soccer Skills from Demonstration

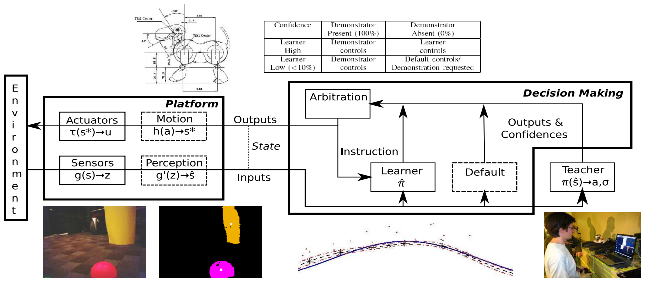
Dan Grollman and Chad Jenkins
Robotics, Learning and Autonomy at Brown
Brown University Department of Computer Science

Abstract:

We seek to enable users to teach personal robots arbitrary tasks so that the robot can better perform as the user desires without explicit programming. Robot learning from demonstration is an approach well-suited to this paradigm, as a robot learns new tasks from observations of the task itself. Many current robot learning algorithms require the existence of basic behaviors that can be combined to perform the desired task. However, robots that exist in the world for long timeframes and learn many tasks over their lifetime may exhaust this basis set and need to move beyond it. In particular, we are interested in a robot that must learn to perform an unknown task for which its built in behaviors may not be appropriate. We demonstrate a learning paradigm that is capable of learning both low-level motion primitives (locomotion and manipulation) and high-level tasks built on top of them from interactive demonstration. We apply nonparametric regression within this framework towards learning a complete robot soccer player and successfully teach a robot dog to first walk, and then to seek and acquire a ball.

Framework:

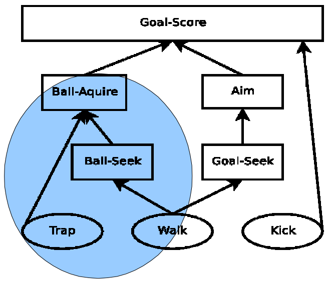
We arbitrate between human-mediated demonstration and autonomous behavior via confidences. The autonomy learns and adapts to the demonstration. A default controller serves to instantiate self-protective instincts and signal when more demonstration is required.



Confidence	Demonstrator Present (100%)	Demonstrator Absent (0%)
Learner High	Demonstrator controls	Learner controls
Learner Low (<10%)	Demonstrator controls	Default controls/ Demonstration requested

Unknown Task:

Robot soccer fieldsman, which can be thought of as floor-level manipulation of balls into goals. This task can be logically decomposed into simpler skills, which are learned first. In this work, we learn the skills indicated in blue.



Learning:

Learning is cast as supervised regression, the goal is to learn a mapping from inputs (perceived states) to outputs (motion commands). We use human-mediated controllers to provide matched input-output pairs. State is 'passed around' to allow for learning without hidden states. We use Sparse Online Gaussian Process (SOGP) regression to perform learning, previous experiments used Locally Weighted Projection Regression (LWPR). Current work focuses on nonparametric techniques that allow for hidden state.

Desired funtional mapping: $\pi(\hat{s}) \rightarrow a - \epsilon$

Symbols

- Motor angles: $\Theta = \{\theta_h, \theta_t \theta_l, \theta_r\}$
- Human-operated joystick: Ω
- Trap Indicator: r
- Color blobs: $\beta = \{h_c, v_c, s_c\}$
- Subtask indicator: Φ

<u>SOGP review</u>

Radial basis function $q(x_i, x_j) = \exp \frac{\|x_i - x_j\|^2}{2\sigma_k^2}$

Covariance Matrix representing learned mapping

$$C_{ij} = q(X_i, X_j) + \delta_{ij}\sigma_v^2$$

Prediction:

$$k_i = q(x', x_i), \hat{y} = k^T C^{-1} Y$$

Variance:

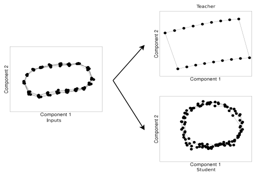
$$\sigma_p^2 = C(p, p)$$

Lowest variance point is discarded for sparsity.

Walk:

Inputs are Motor Angles and Human-operated joysticks. Outputs are desired Motor Angles. The demonstrated walk is open-loop and uses state inaccessible to the learner. The learned gait is closed loop and more closely reflects the observed behavior.

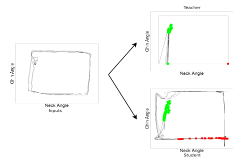
$$\pi(\Theta, \Omega) \rightarrow \Theta$$



Trap:

Using the motors of the head and mouth, grasp the ball and detect success / failure. Green circles indicate success and red squares, failure.

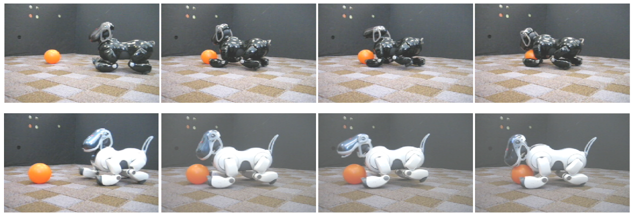
$$\pi(\theta_h) \rightarrow \theta_h, r$$



Acquire:

Using color blobs, modulate the walk to approach the ball. When in range, use the trapping motion grasp it. One bit of state is necessary to disambiguate sensor inputs. Shown are frames from videos of this task being taught (black dog) and performed as learned (white dog).

$$\pi(\theta_h, \beta, \Phi) \rightarrow \Omega, \theta_h, \Phi$$



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