Application Considerations for the DHP Methodology

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SESSION on “Intelligent” Control

Generally, the human designer of the control system has lots of work to do before turning (remainder of) the design task over to our “intelligent” (aka: Neural Networks?) controller.

We here ASSUME that many design decisions have already been made:

e.g.

- need for reinforcement learning approach (due to absence of certain otherwise needed information)
- representation of plant (state?) variables/ measurables
- criterion function (re. "desired" qualities)
- basic architecture of controller neural network

Context (re. Reinforcement Learning):

<u>Adaptive Critic Design (ACD)</u>

A methodology for adaptively designing an (approximately) optimal controller for a given plant according to a stated criterion.

We use a NN as the controller [actionNN], and another NN [criticNN] to update (assist in the design of) the controller.

"Plant" is represented via state vector R(t).

Context:

The ACD method entails the user defining a (primary) utility function $U(t)$ for the specific application, and then maximizing a new utility function (Bellman Eqn.):

$$J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k)$$

[We note: $J(t) = U(t) + \gamma J(t+1)$

Context: Family of Adaptive Critic Designs

The criticNN approximates either $J(t)$ or gradient of $J(t)$ wrt state vector $R(t)$ $[\nabla J(R)]$

❖Heuristic Dynamic Programming (HDP)

CriticNN approximates $J(t)$

❖Dual Heuristic Programming (DHP)

CriticNN approximates $\nabla J(R) \equiv \lambda$

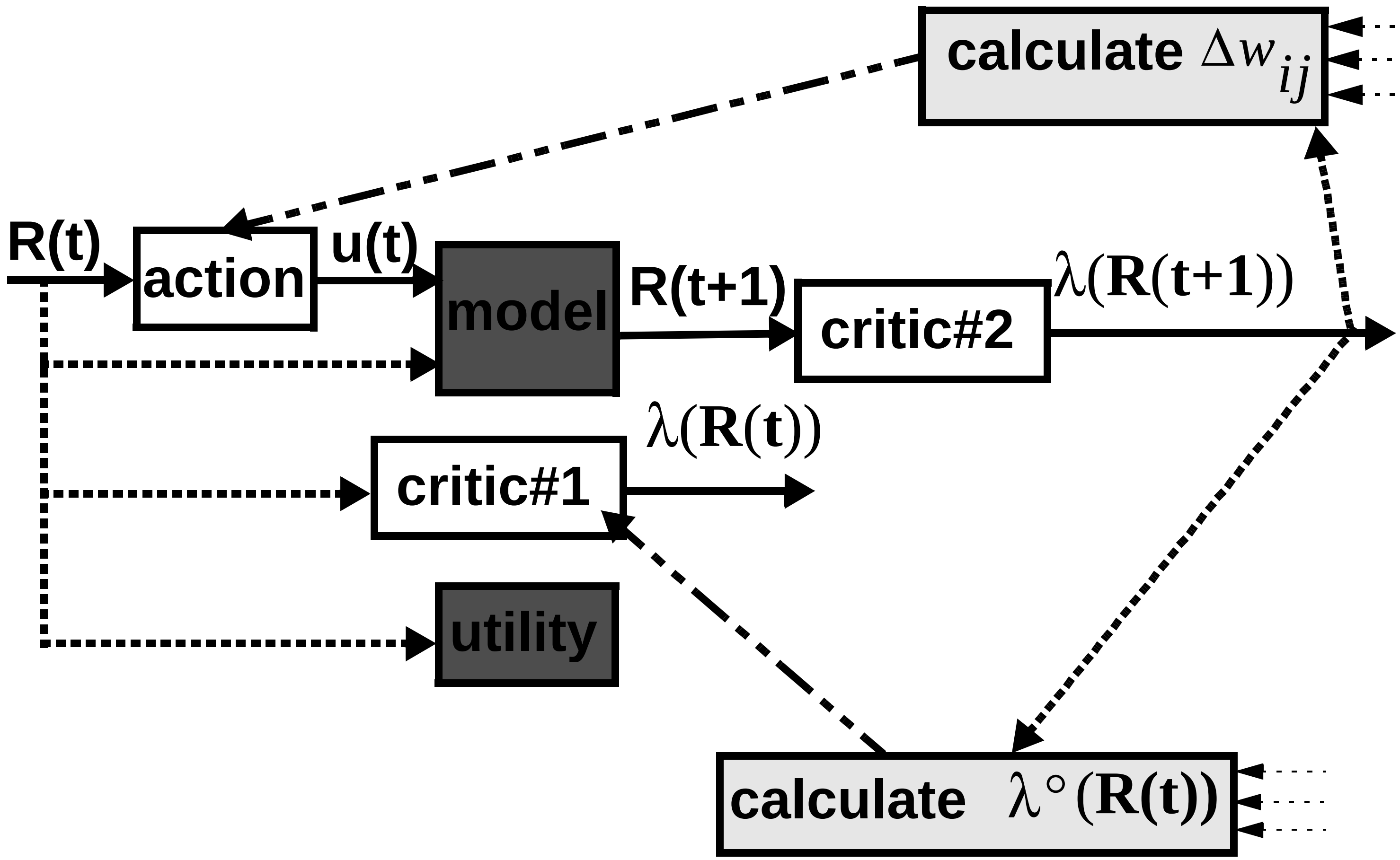
❖Generalized Dual HeuristicProgramming(GDHP)

CriticNN approximates $J(t)$ and $\nabla J(R)$

❖Action Dependent ....

CriticNN also inputs $u(t)$ and outputs$\nabla J(u)$

Computing Schema for discussing Strategies



Weights in actionNN are updated with objective of maximizing J(t):

$$\Delta w_{ij}(t) = lcoef \bullet \frac{\partial}{\partial w_{ij}(t)} J(t)$$

where

$$\frac{\partial}{\partial w_{ij}(t)} J(t) = \sum_{k=1}^{u} \frac{\partial}{\partial u_k(t)} J(t) \bullet \frac{\partial}{\partial w_{ij}(t)} u_k(t)$$

and

$$\frac{\partial}{\partial u_k(t)} J(t) = \frac{\partial}{\partial u_k(t)} U(t) + \frac{\partial}{\partial u_k(t)} J(t+1)$$

and

$$\frac{\partial}{\partial u_k(t)} J(t+1) = \sum_{s=1}^{n} \frac{\partial}{\partial R_s(t+1)} J(t+1) \bullet \frac{\partial}{\partial u_k(t)} R_s(t+1)$$

call this term $\lambda(t+1)$ **(to be output of critic)**

CriticNN output is λ.

For training criticNN, “desired output” is λ°.

(cf. Eqn. (6) in paper)

Paraphrase of Eqn. (6) [cf. Eqn. (7) in paper]:

$$\lambda_s^\circ(t) = [\sim\text{Utility}] + \sum_{j=1}^{a} ([\sim\text{Utility}] \bullet [\sim\text{Action}])$$

$$+ \sum_{k=1}^{n} ([\sim\text{Critic(t+1)}] \bullet [\sim\text{Plant}])$$

$$+ \sum_{k=1}^{n} \left\{ \sum_{j=1}^{a} ([\sim\text{Critic(t+1)}] \bullet [\sim\text{Plant}] \bullet [\sim\text{Action}]) \right\}$$

Strategies to solve Eqn. (6) [and (7)]

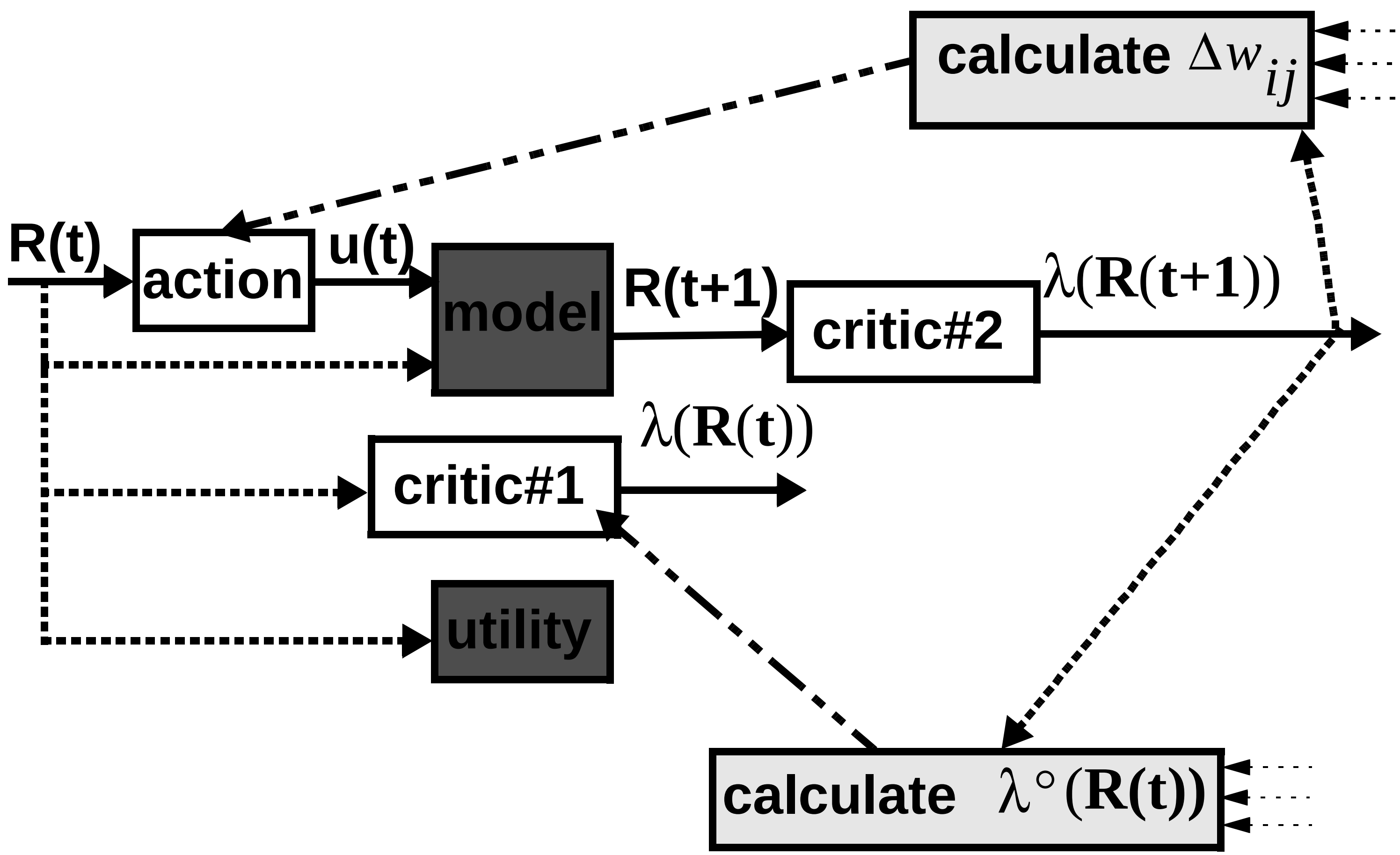
Strategy 1. Straight application of the equation.

Strategy 2. Basic 2-stage process [“flip/flop”].
[e.g., Santiago/Werbos, Prokhorov/Wunsch]
During stage 1, train criticNN, not actionNN;
During stage 2, train actionNN, not criticNN.

Strategy 3. Modified 1st stage of 2-stage process.
While train criticNN during stage 1, keep parameters constant in module that calculates critic’s desired output $\lambda^{\circ}(\mathbf{R})$. Then adjust weights all at once at end of stage 1.

Strategy 4. Single-stage process, using modifications introduced in Strategy 3.

Computing Schema for discussing Strategies



Recap re. criticNN:

Performs mapping: $\lambda(\mathbf{R})$

Desired output for training purposes: $\lambda^{\circ}(\mathbf{R})$

Solution (not known) of Bellman equation: λ^$(\mathbf{R})$

Learn process: $\lambda(\mathbf{R})$ **is to converge to** $\lambda^{\circ}(\mathbf{R})$;

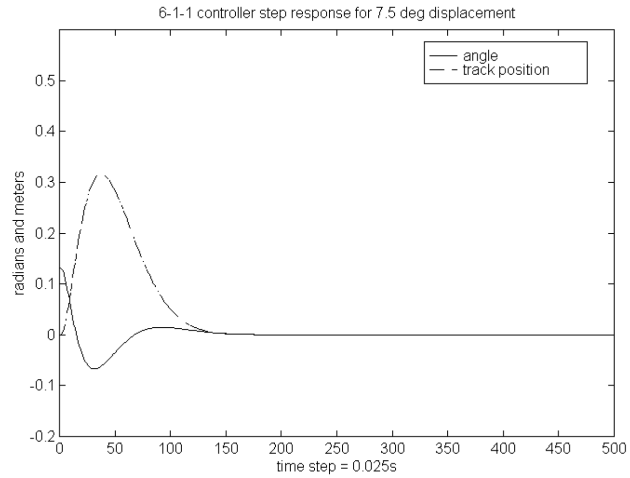
$\lambda^{\circ}(\mathbf{R})$ **is to converge to** λ^$(\mathbf{R})$.

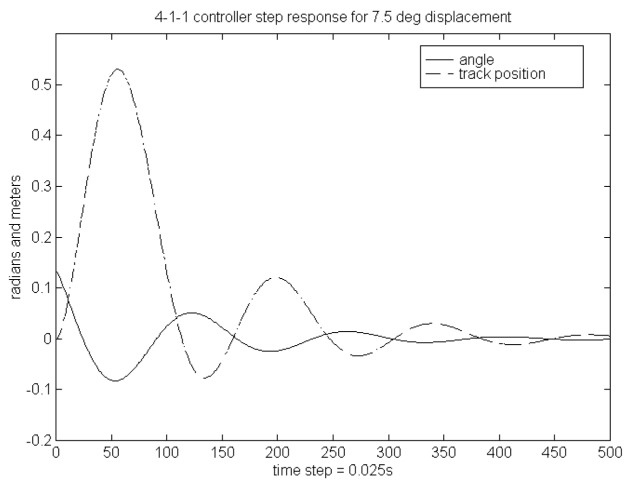
i.e., $\lambda(\mathbf{R})$ $\lambda^{\circ}(\mathbf{R})$ λ^$(\mathbf{R})$

[The better the criticNN "solves" the Bellman eqn., the better the actionNN will approximate an optimal controller.]

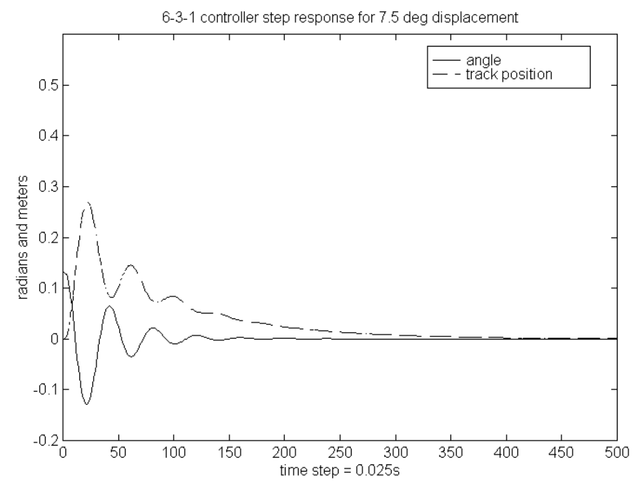
Step Responses to 7.5^{o} pole displacement

6-1-1 Controller





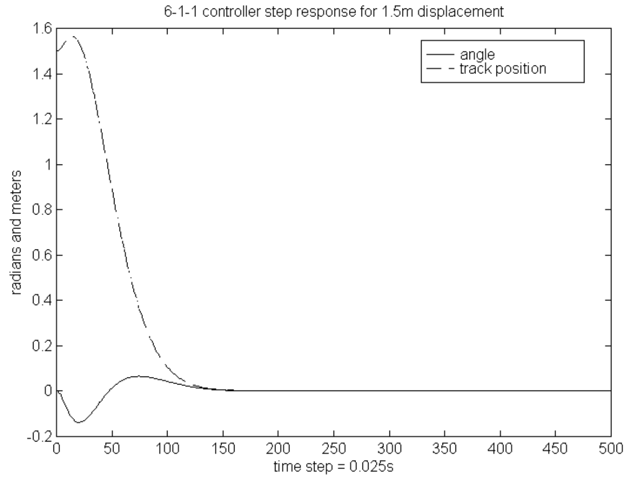
4-1-1 Controller

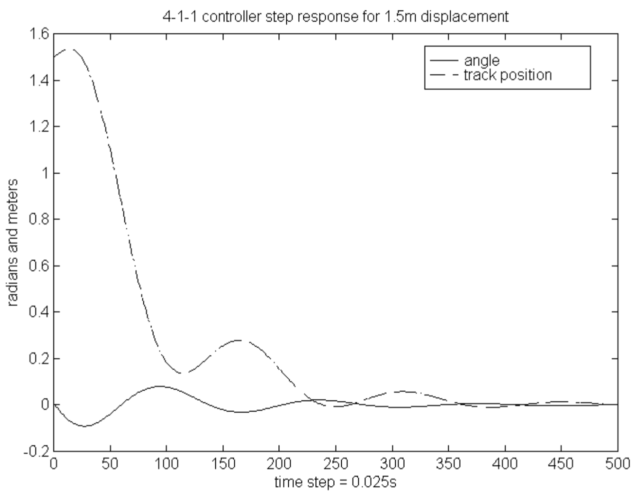


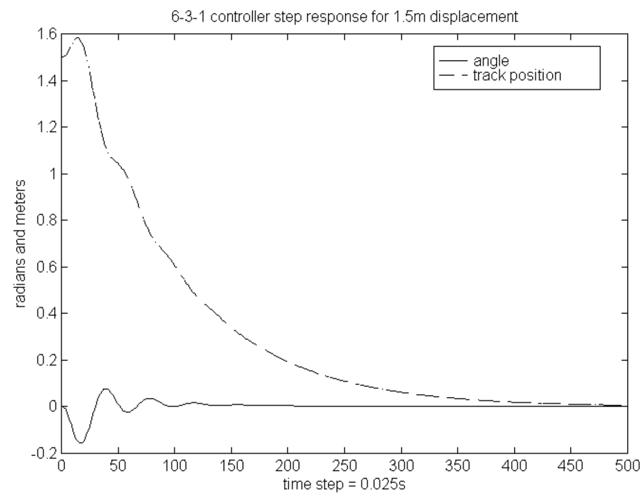
6-3-1 Controller

Step Responses to 1.5m cart displacement

6-1-1 Controller







4-1-1 Controller

6-3-1 Controller

Step Responses of 6-1-1 Controller, 1m pole

[Trained w/ max ± 10^o]

[No explicit X training]

Trained: 7.5^{o}displ.

Tested: 38^{o}displ.

Tested: -6.6m displ.