CSCE 790: Neural Networks and Their Applications AIISC and Dept. Computer Science and Engineering Email: vignar@sc.edu

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October 10, 2023

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Hopfield Network

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Neural Processing Elements (NPE)

Figure: NPE - Continuous time units (Lewis, '99)

$$
y_i(t) = \sum_{j=1}^n w_{ij} \sigma_j(x_j)(t), \quad \tau_i \dot{x}_i(t) = -x_i(t) + \sum_{j=1}^n w_{ij} \sigma_j(x_j)(t) + v_{ii} u_i
$$

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DT - Neural Processing Elements (NPE)

Figure: NPE - Discrete time units (Lewis, '99)

$$
y_i(k) = \sum_{j=1}^n w_{ij} \sigma_j(x_j)(k), \quad x_i(k+1) = p_i x_i(k) + \sum_{j=1}^n w_{ij} \sigma_j(x_j)(k) + v_{ii} u_i
$$

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Hopfield Networks

Figure: Hopfield network with NPE (Lewis, '99)

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Generalized Recurrent Neural Network

Figure: Generalized recurrent neural networks (Lewis, '99)

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Direct Computation of Weights for Hopfield Network

- In the Hopfield net, the weights can be initialized by direct computation of outer products between desired outputs
- Suppose we would like to design a Hopfield network that can classify or discriminate between P given bipolar pattern $\{X^1, X^2, \ldots, X^P\}$ each having n entries of either $+1$ or -1
- Given $x(0)$ as initial condition (input), the Hopfield network should perform association and match the input with one of the P patterns

Hopfield Weight Selection

• Hopfield showed that weights to solve this problem may be selected by using the Hebbian philosophy of learning as the outer product of \mathcal{X}^P

$$
W = \frac{1}{n} \sum_{p=1}^{P} X^{P} (X^{P})' - \frac{1}{n} P I,
$$

- \bullet / is the identity matrix
- The purpose of the term PI is to zero out the diagonal
- Note that this weight matrix W is symmetric
- This formula effectively encodes the exemplar patterns in the weights of the NN
- Though there is no weight tuning, technically this formula is an example of supervised learning, as the desired outputs are used to compute the weights

Example

Example

Consider a Hopfield network

$$
\dot{x}(t) = -\frac{1}{2}x(t) + \frac{1}{2}W'\sigma(x(t)) + \frac{1}{2}u,
$$

with $x(t)\in\mathbb{R}^2$ and a symmetric sigmoid function

$$
\sigma(x_i) = \frac{1 - e^{-100x_i}}{1 + e^{-100x_i}}.
$$

Suppose the prescribed exemplar patterns are $X^1=(1,1)^{\prime}$ and $X^2=(-1,-1)^{\prime}$. $(u=0)$

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Example

Figure: Symmetric Sigmoid Figure: Trajectories of the Hopfield networks

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Backpropagation Through Time (wiki)

• Backpropagation through time (BPTT) for training certain types of recurrent neural networks is an analogue to Backpropagation algorithm for training feedforward neural networks

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Figure: Backpropagation through time (wiki)

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- \bullet In the example the neural network contains a recurrent layer f and a feedforward layer g
- Training cost can be defined in various way
- Example: Aggregated cost average of the costs of each time steps
- In the figure the cost at time $t + 3$ is show by unfolding the recurrent layer f for three time steps and adding the feedforward layer g
- \bullet Each instance of f in the unfolded network shares the same parameters
- Thus the weight updates in each instance f_1, f_2, f_3 are summed together

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NN Application for Control - Learning Paradigm - "Reinforcement Learning"

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- Recall the problem of Control design:
- Example: Cruise control problem for a toy car model

$$
\dot{x}(t) = -\frac{c}{m}u(t), \quad x(0) \in \mathbb{R}^+, \tag{1}
$$

where $x(t)$ is the velocity of the car at time t.

• What happens to this system when a proportional control input $u(t) = Kx(t)$ is selected $(K > 0)$?

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Reference Tracking Problem

- Given a reference/desired velocity $r(t)$, what should be the control input so that the car moves with the given velocity?
- Define the error, i.e., the difference between the reference velocity and the actual velocity as

$$
e(t) = r(t) - x(t)
$$

• Compute how this error changes with time,

$$
\dot{e}(t)=\dot{r}(t)-\dot{x}(t)=\dot{r}(t)+\frac{c}{m}u(t),
$$

• How to design control input for this case?

- Recall the problem of Control design:
- Example: Cruise control problem for a toy car model

$$
\dot{x}(t) = -\frac{c}{m}u(t), \quad x(0) \in \mathbb{R}^+, \tag{2}
$$

where $x(t)$ is the velocity of the car at time t.

• What happens to this system when a proportional control input $u(t) = Kx(t)$ is selected $(K > 0)$?

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- Given a reference/desired velocity $r(t)$, what should be the control input so that the car moves with the given velocity?
- Define the error, i.e., the difference between the reference velocity and the actual velocity as

 $e(t) = r(t) - x(t)$

• Compute how this error changes with time,

$$
\dot{e}(t)=\dot{r}(t)-\dot{x}(t)=\dot{r}(t)+\frac{c}{m}u(t),
$$

• How to design control input for this case?

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- Given a constant or fixed reference/desired velocity, i.e., $r(t) = R$ for all $t > 0$, what should be the control input so that the car moves with the given velocity?
- Define the error, i.e., the difference between the reference velocity and the actual velocity as

$$
e(t)=R-x(t)
$$

• Compute how this error changes with time,

$$
\dot{e}(t)=\dot{R}-\dot{x}(t)=0+\frac{c}{m}u(t),
$$

• How to design control input for this case?

Example: Robotic System

Figure: Robotic Systems (wiki). SKYWASH, DaVinci AEG, Dornier, Fraunhofer Institute, Putzmeister - Germany Using 2 Skywash robots for cleaning a Boeing 747-400 jumbo jet, its grounding time is reduced from 9 to 3.5 hours. The world´s largest cleaning brush travels a distance of approximately 3.8 kilometers and covers a surface of around 2,400 m² which is about 85% of the entire plane 's surface area. The kinematics consist of 5 main joints for the robot 's arm, and an additional one for the turning circle of the rotating washing brush. The Skywash includes database that contains the aircraft-specific geometrical data. A 3-D distance camera accurately positions the mobile robot next to the aircraft. The 3-D camera and the computer determine the aircraft´s ideal positioning, and thus the cleaning process begins. QQ

Example

Figure: Medical Robotics

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Figure: Block diagram of a feedback control system

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- **o** Given
	- The desired or the reference trajectory for the robotic system to track
	- Measurements from the sensor informing the actual path/trajectory of the robotic system
- To Do
	- Design control inputs or policies that steers the actual path traced by the robotic system is close to the reference trajectory

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Physics-based Model

e Robotic arm

$$
M(q)\ddot{q}(t)+V_m(q,\dot{q})+G(q)+F(q,\dot{q})=\tau(t)+\tau_d(t)
$$

- Dynamic Equations Newton-Euler method or Lagrangian Dynamics
- $q(t)$ Joint variable
- \bullet $M(q)$ Models of inertial mass
- \bullet $V_m(q,q)$ Models of coriolis/centripetal force
- \bullet $F(q, \dot{q})$ Models of friction
- \bullet $G(q)$ models of Gravity
- **•** *τ*(*t*) Control torque
- \bullet $\tau_d(t)$ models of disturbance

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Tracking Control Problem

- Let the desired trajectory for the robot manipulator be $q_d(t)$
- Now, we can define the tracking error as

$$
e(t) = q_d(t) - q(t)
$$

• Define the filtered tracking error as

$$
r(t) = e(t) + \lambda e(t)
$$

• Filtered tracking error dynamics

$$
\dot{r}(t) = \ddot{e}(t) + \lambda \dot{e}(t)
$$

Tracking Control Problem

- Filtered tracking error dynamics are: $\dot{r}(t) = \ddot{e}(t) + \lambda \dot{e}(t)$
- Recall the robot dynamics: $M(q)\ddot{q}(t) + V_m(q, \dot{q}) + G(q) + F(q, \dot{q}) = \tau(t) + \tau_d(t)$

$$
Mi(t) = -V_{m}r(t) - \tau(t) + h + \tau_d(t)
$$

$$
h = M(q)(\ddot{q}_d + \lambda \dot{e}) + V_m(q, \dot{q})(\dot{q}_d + \lambda e) + F(\dot{q}) + G(q)
$$

Control Torque

$$
\tau(t)=\hat{h}+{\sf K}_{{\sf v}} r(t)
$$

with λ , K_v being a positive design parameter

• The closed-loop dynamics is obtained as

$$
Mi(t) = -V_m r(t) - \hat{h} - K_v r(t) + h + \tau_d(t)
$$

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NN Control - Function Approximator

Figure: Feedback NN control

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Steady-State Analysis of Feedback Control System

• Filtered tracking error dynamics

$$
\dot{r}(t) = -\frac{V_m - K_v}{M}r(t) + \frac{h - \hat{h}}{M} + \frac{\tau_d(t)}{M}
$$

$$
\dot{r}(t) = -Kr(t) + N_{\varepsilon} + d(t)
$$

What does the Lyapunov approach reveal?

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