

Slide10

Haykin Chapter 14: Neurodynamics (3rd Ed. Chapter 13)

CPSC 636-600

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Stability in Nonlinear Dynamical System

- **Lyapunov stability:** more on this later.
- Study of neurodynamics:
 - Deterministic neurodynamics: expressed as nonlinear differential equations.
 - Stochastic neurodynamics: expressed in terms of stochastic nonlinear differential equations. Recurrent networks perturbed by noise.

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Neural Networks with Temporal Behavior

- Inclusion of feedback gives temporal characteristics to neural networks: **recurrent networks**.
- Two ways to add feedback:
 - Local feedback
 - Global feedback
- Recurrent networks can become unstable or stable.
- Main interest is in recurrent network's **stability: neurodynamics**.
- Stability is a property of the *whole system*: coordination between parts is necessary.

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Preliminaries: Dynamical Systems

- A **dynamical system** is a system whose state varies with time.
- **State-space model:** values of state variables change over time.
- Example: $x_1(t), x_2(t), \dots, x_N(t)$ are state variables that hold different values under *independent variable* t . This describes a system of *order* N , and $\mathbf{x}(t)$ is called the *state vector*. The dynamics of the system is expressed using ordinary differential equations:

$$\frac{d}{dt}x_j(t) = F_j(x_j(t)), j = 1, 2, \dots, N.$$

or, more conveniently

$$\frac{d}{dt}\mathbf{x}(t) = \mathbf{F}(\mathbf{x}(t)).$$

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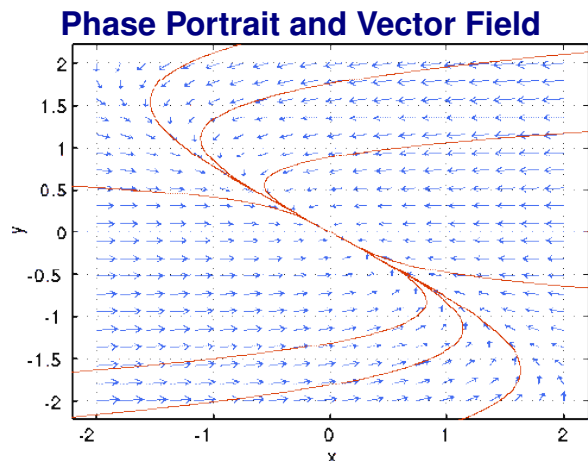
Autonomous vs. Non-autonomous Dynamical Systems

- Autonomous: $\mathbf{F}(\cdot)$ does not explicitly depend on time.
- Non-autonomous: $\mathbf{F}(\cdot)$ explicitly depends on time.

\mathbf{F} as a Vector Field

- Since $\frac{d\mathbf{x}}{dt}$ can be seen as velocity, $\mathbf{F}(\mathbf{x})$ can be seen as a velocity vector field, or a vector field.
- In a vector field, each point in space (\mathbf{x}) is associated with one unique vector (direction and magnitude). In a scalar field, one point has one scalar value.

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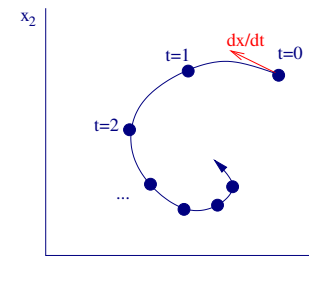


- Red curves show the state (phase) portrait represented by trajectories from different initial points.
- The blue arrows in the background shows the vector field.

Source: http://www.math.ku.edu/~byers/ode/b_cp_lab/pict.html

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State Space



- It is convenient to view the state-space equation $\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x})$ as describing the **motion** of a point in N-dimensional space (Euclidean or non-Euclidean). Note: t is continuous!
- The points traversed over time is called the **trajectory** or the **orbit**.
- The **tangent vector** shows the instantaneous velocity at the initial condition.

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Conditions for the Solution of the State Space Equation

- A unique solution to the state space equation exists only under certain conditions, which restricts the form of $\mathbf{F}(\mathbf{x})$.
- For a solution to exist, it is sufficient for $\mathbf{F}(\mathbf{x})$ to be continuous in all of its arguments.
- For uniqueness, it must meet the **Lipschitz condition**.
- Lipschitz condition:
 - Let \mathbf{x} and \mathbf{u} be a pair of vectors in an open set \mathcal{M} in a normal vector space. A vector function $\mathbf{F}(\mathbf{x})$ that satisfies:

$$\|\mathbf{F}(\mathbf{x}) - \mathbf{F}(\mathbf{u})\| \leq K\|\mathbf{x} - \mathbf{u}\|$$

for some constant K , the above is said to be **Lipschitz**, and K is called the Lipschitz constant for $\mathbf{F}(\mathbf{x})$.

- If $\partial F_i / \partial x_j$ are finite everywhere, $\mathbf{F}(\mathbf{x})$ meet the Lipschitz condition.

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Stability of Equilibrium States

- $\bar{\mathbf{x}} \in \mathcal{M}$ is said to be an *equilibrium state* (or singular point) of the system if

$$\left. \frac{d\mathbf{x}}{dt} \right|_{\mathbf{x}=\bar{\mathbf{x}}} = \mathbf{F}(\bar{\mathbf{x}}) = \mathbf{0}.$$

- How the system behaves near these equilibrium states is of great interest.
- Near these points, we can approximate the dynamics by **linearizing** $\mathbf{F}(\mathbf{x})$ (using Taylor expansion) around $\bar{\mathbf{x}}$, i.e., $\mathbf{x}(t) = \bar{\mathbf{x}} + \Delta\mathbf{x}(t)$:

$$\mathbf{F}(\mathbf{x}) \approx \bar{\mathbf{x}} + \mathbf{A}\Delta\mathbf{x}(t)$$

where \mathbf{A} is the Jacobian:

$$\mathbf{A} = \left. \frac{\partial}{\partial \mathbf{x}} \mathbf{F}(\mathbf{x}) \right|_{\mathbf{x}=\bar{\mathbf{x}}}$$

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Eigenvalues/Eigenvectors

- For a square matrix \mathbf{A} , if a vector \mathbf{x} and a scalar value λ exists so that

$$(\mathbf{A} - \lambda\mathbf{I})\mathbf{x} = \mathbf{0}$$

then \mathbf{x} is called an **eigenvector** of \mathbf{A} and λ an **eigenvalue**.

- Note, the above is simply

$$\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$$

- An intuitive meaning is: \mathbf{x} is the direction in which applying the linear transformation \mathbf{A} only changes the magnitude of \mathbf{x} (by λ) but not the angle.
- There can be as many as n eigenvector/eigenvalue for an $n \times n$ matrix.

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Stability of in Linearized System

- In the linearized system, the property of the Jacobian matrix \mathbf{A} determine the behavior near equilibrium points.

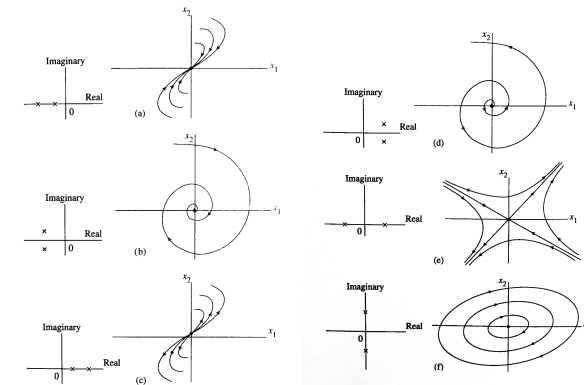
- This is because

$$\frac{d}{dt} \Delta\mathbf{x}(t) \approx \mathbf{A}\Delta\mathbf{x}(t).$$

- If \mathbf{A} is nonsingular, \mathbf{A}^{-1} exists and this can be used to describe the **local** behavior near the equilibrium $\bar{\mathbf{x}}$.
- The eigenvalues of the matrix \mathbf{A} characterize different classes of behaviors.

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Example: 2nd-Order System



Positive/negative, real/imaginary character of **eigenvalues** of Jacobian determine behavior.

- Stable node (real -), unstable focus (Complex, + real)
- Stable focus (Complex, - real), Saddle point (real + -)
- Unstable node (real +), Center (Complex, 0 real)

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Definitions of Stability

- **Uniformly stable** for an arbitrary $\epsilon > 0$, if there exists a positive δ such that $\|\mathbf{x}(0) - \bar{\mathbf{x}}\| < \delta$ implies $\|\mathbf{x}(t) - \bar{\mathbf{x}}\| < \epsilon$ for all $t > 0$.
- **Convergent** if there exists a positive δ such that $\|\mathbf{x}(0) - \bar{\mathbf{x}}\| < \delta$ implies $\mathbf{x}(t) \rightarrow \bar{\mathbf{x}}$ as $t \rightarrow \infty$
- **Asymptotically stable** if both stable and convergent.
- **Globally asymptotically stable** if stable and all trajectories of the system converge to $\bar{\mathbf{x}}$ as time t approaches infinity.

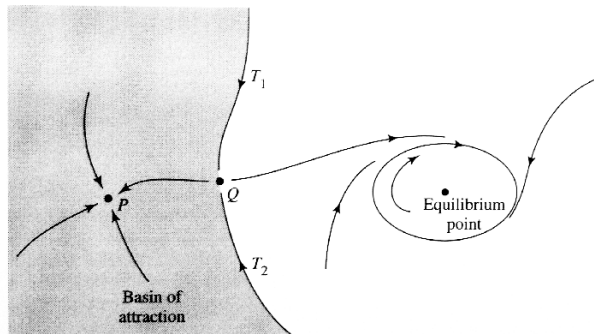
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Lyapunov's Theorem

- **Theorem 1:** The equilibrium state $\bar{\mathbf{x}}$ is stable if in a small neighborhood of $\bar{\mathbf{x}}$ there exists a positive definite function $V(\mathbf{x})$ such that its derivative with respect to time is negative semidefinite in that region.
- **Theorem 2:** The equilibrium state $\bar{\mathbf{x}}$ is asymptotically stable if in a small neighborhood of $\bar{\mathbf{x}}$ there exists a positive definite function $V(\mathbf{x})$ such that its derivative with respect to time is negative definite in that region.
- A scalar function $V(\mathbf{x})$ that satisfies these conditions is called a **Lyapunov function** for the equilibrium state $\bar{\mathbf{x}}$.

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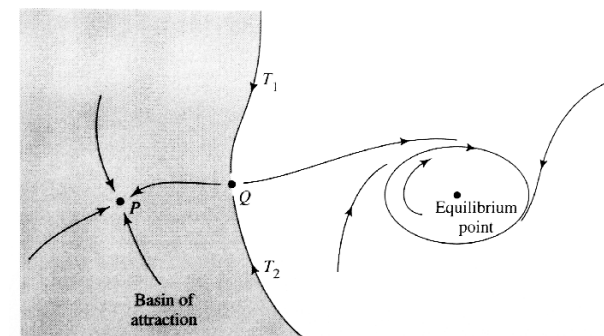
Attractors



- Dissipative systems are characterized by attracting sets or manifolds of dimensionality lower than that of the embedding space. These are called **attractors**.
- *Regions* of initial conditions of nonzero state space volume *converge* to these attractors as time t increases.

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Types of Attractors



- Point attractors (left)
- Limit cycle attractors (right)
- Strange (chaotic) attractors (not shown)

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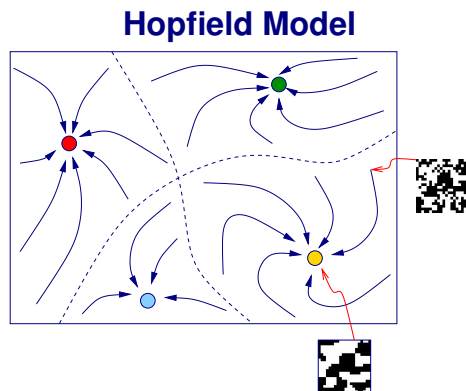
Neurodynamical Models

We will focus on state variables are continuous-valued, and those with dynamics expressed in differential equations or difference equations.

Properties:

- Large number of degree of freedom.
- Nonlinearity
- Dissipative (as opposed to conservative), i.e., open system.
- Noise

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- N units with full connection among every node (no self-feedback).
- Given M input patterns, each having the same dimensionality as the network, can be memorized in attractors of the network.
- Starting with an initial pattern, the dynamic will converge toward the attractor of the basin of attraction where the initial pattern was placed.

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Manipulation of Attractors as a Recurrent Nnet Paradigm

- We can identify attractors with computational objects (associative memories, input-output mappers, etc.).
- In order to do so, we must exercise *control* over the location of the attractors in the state space of the system.
- A learning algorithm will manipulate the equations governing the dynamical behavior so that a desired location of attractors are set.
- One good way to do this is to use the **energy minimization** paradigm (e.g., by Hopfield).

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Discrete Hopfield Model

- Based on McCulloch-Pitts model (neurons with +1 or -1 output).
- Energy function is defined as

$$E = -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N w_{ji} x_i x_j (i \neq j).$$

- Network dynamics will evolve in the direction that minimizes E .
- Implements a **content-addressable memory**.

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Content-Addressable Memory

- Map a set of patterns to be memorized ξ_μ onto fixed points \mathbf{x}_μ in the dynamical system realized by the recurrent network.
- **Encoding**: Mapping from ξ_μ to \mathbf{x}_μ
- **Decoding**: Reverse mapping from state space \mathbf{x}_μ to ξ_μ .

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Hopfield Model: Activation (Retrieval)

- Initialize the network with a **probe pattern** ξ_{probe} .

$$x_j(0) = \xi_{\text{probe},j}.$$

- Update output of each neuron (picking them by random) as

$$x_j(n+1) = \text{sgn} \left(\sum_{i=1}^N w_{ji} x_i(n) \right).$$

until \mathbf{x} reaches a fixed point.

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Hopfield Model: Storage

- The learning is similar to Hebbian learning:

$$w_{ji} = \frac{1}{N} \sum_{\mu=1}^M \xi_{\mu,j} \xi_{\mu,i}$$

with $w_{ji} = 0$ if $i = j$. (Learning is **one-shot**.)

- In matrix form the above becomes:

$$\mathbf{W} = \frac{1}{N} \sum_{\mu=1}^M \xi_\mu \xi_\mu^T - M\mathbf{I}$$

- The resulting weight matrix \mathbf{W} is symmetric: $\mathbf{W} = \mathbf{W}^T$.

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Spurious States

- The weight matrix \mathbf{W} is symmetric, thus the eigenvalues of \mathbf{W} are all real.
- For large number of patterns M , the matrix is *degenerate*, i.e., several eigenvectors can have the same eigenvalue.
- These eigenvectors form a subspace, and when the associated eigenvalue is 0, it is called a *null space*.
- This is due to M being smaller than the number of neurons N .
- Hopfield network as content addressable memory:
 - Discrete Hopfield network acts as a vector projector (project probe vector onto subspace spanned by training patterns).
 - Underlying dynamics drive the network to converge to one of the corners of the unit hypercube.
- **Spurious states** are those corners of the hypercube that do not belong to the training pattern set.

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Storage Capacity of Hopfield Network

- Given a probe equal to the stored pattern ξ_{ν} , the activation of the j th neuron can be decomposed into the signal term and the noise term:

$$\begin{aligned}
 v_j &= \sum_{i=1}^N w_{ji} \xi_{\nu,i} \\
 &= \frac{1}{N} \sum_{\mu=1}^M \xi_{\mu,j} \sum_{i=1}^N \xi_{\mu,i} \xi_{\nu,i} \\
 &= \underbrace{\xi_{\nu,j}}_{\text{signal } (\xi_{\nu,j}^3 = \xi_{\nu,j} \in \{\pm 1\})} + \underbrace{\frac{1}{N} \sum_{\mu=1, \mu \neq \nu}^M \xi_{\mu,j} \sum_{i=1}^N \xi_{\mu,i} \xi_{\nu,i}}_{\text{noise}}
 \end{aligned}$$

- The *signal-to-noise ratio* is defined as

$$\rho = \frac{\text{variance of signal}}{\text{variance of noise}} = \frac{1}{(M-1)/N} \approx \frac{N}{M}$$

- The reciprocal of ρ , called the *load parameter* is designated as α . According to Amit and others, this value needs to be less than 0.14 (critical value α_c).

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Cohen-Grossberg Theorem

- Cohen and Grossberg (1983) showed how to assess the stability of a certain class of neural networks:

$$\frac{d}{dt} u_j = a_j(u_j) \left[b_j(u_j) - \sum_{i=1}^N c_{ji} \varphi_i(u_i) \right], j = 1, 2, \dots, N$$

- Neural network with the above dynamics admits a Lyapunov function defined as:

$$E = \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N c_{ji} \varphi_i(u_i) \varphi_j(u_j) - \sum_{j=1}^N \int_0^{u_j} b_j(\lambda) \varphi_j'(\lambda) d\lambda,$$

where

$$\varphi_j'(\lambda) = \frac{d}{d\lambda} (\varphi_j(\lambda)).$$

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Storage Capacity of Hopfield Network (cont'd)

- Given $\alpha = 0.14$, the storage capacity becomes

$$M_c = \alpha_c N = 0.14N$$

when some error is allowed in the final patterns.

- For almost error-free performance, the storage capacity become

$$M_c = \frac{N}{2 \log_e N}$$

- Thus, storage capacity of Hopfield network scales less than linearly with the size N of the network.
- This is a major limitation of the Hopfield model.

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Cohen-Grossberg Theorem (cont'd)

- For the definition in the previous slide to be valid, the following conditions need to be met.
 - The synaptic weights are symmetric.
 - The function $a_j(u_j)$ satisfies the condition for *nonnegativity*.
 - The nonlinear activation function $\varphi_j(u_j)$ needs to follow the *monotonicity condition*:

$$\varphi_j'(u_j) = \frac{d}{du_j} \varphi_j(u_j) \geq 0.$$

- With the above

$$\frac{dE}{dt} \leq 0$$

ensuring global stability of the system.

- Hopfield model can be seen as a special case of the Cohen-Grossberg theorem.

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Demo

- Noisy input
- Partial input
- Capacity overload