### Symmetry in Complex Systems

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#### Computational Science Research Center, 2009

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## Smell: Meet Yogi



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#### **Electrosensors: Sharks**



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# Sight: Fly Eye



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#### **PSD** Detection



Figure: Without External Signal



Figure: With External Signal

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#### **Residence Times Detection**



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Figure: Complex Systems

#### Definition

"A complex system is a system composed of interconnected parts that as a whole exhibit one or more properties (behavior among the possible properties) not obvious from the properties of the individual parts." (Wikipedia).

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#### General Approach

A general approach for the analysis of complex systems has been to derive a detailed model of the individual parts, connect the parts and note that the system contains some sort of symmetry, then attempt to exploit this symmetry in order to simplify numerical computations.

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Theoretical Analysis Hardware Realization Validation

# Outline

- 3 Electric-Field Sensors Theoretical Analysis Hardware Realization Modeling General Approach
  - Symmetry Approach

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#### Model Equations

$$\tau \dot{x}_i = ax_i - bx_i^3 + \lambda(x_i - x_{i+1}) + \varepsilon, \qquad i = 1, 2, \dots, N \mod N$$

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#### **One-Parameter Bifurcation Analysis**



#### Figure: Bifurcation Diagram



#### Figure: Phase-Space

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#### Two-Parameter Bifurcation Analysis



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#### Time-Periodic Target Signal

#### **Model Equations**

$$\tau \dot{x}_i = ax_i - bx_i^3 + \lambda(x_i - x_{i+1}) + \varepsilon \sin(\omega t).$$

# Asymptotic Analysis via Airy Functions $\varepsilon_{c} = \frac{F_{0} - \lambda e}{1 + \lambda f}$ $\varepsilon_{c} = \frac{2(F_{0} - \lambda e)(1 + \lambda f) + k_{1}^{3}(1 - \lambda f)\Omega^{2}}{2(1 + \lambda f)^{2}} \pm \frac{\sqrt{k_{1}^{3}\Omega^{2}(8(F_{0} - \lambda e)(1 + \lambda f) - k_{1}^{3}\Omega^{2}(1 - \lambda f))}}{2(1 + \lambda f)^{2}}$



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#### Hardware Dynamics

$$C_L \dot{V}_i = -gV_i + I_s anh[c_sV_i] + I_c anh[c_cV_{i-1}] - \varepsilon$$



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#### **One-Parameter Bifurcation Diagrams**





Figure: Theory

Figure: Experiment

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#### Two-Parameter Bifurcation Diagrams



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#### **Time-Series Oscillations**





#### Figure: Experiment

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Figure: Theory

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Frequency and RTD Response



Figure: Theory



Figure: Experiment

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Modeling General Approach Symmetry Approach

# Outline

- Best Sensory Systems
- 2 Complex Systems
- 3 Electric-Field Sensors
  - Theoretical Analysis
  - Hardware Realization
  - Validation
- Oupled Inertial Navigation System
  - Modeling
  - General Approach
  - Symmetry Approach

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#### **Equations of Motion**

$$\begin{split} m\ddot{x}_{j} + c\dot{x}_{j} + \kappa x_{j} + \mu x_{j}^{3} &= A_{d} \sin w_{d} t + 2m\Omega_{z}\dot{y}_{j} + \sum_{k \to j} c_{jk}h(x_{j}, x_{k}) \\ m\ddot{y}_{j} + c\dot{y}_{j} + \kappa y_{j} + \mu y_{j}^{3} &= -2m\Omega_{z}\dot{x}_{j}, \end{split}$$

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#### Van der Pol Transformations

$$\begin{array}{rcl} u_{1j} &=& x_j \cos w\tau - \dot{x}_j / w \sin w\tau, \\ u_{2j} &=& -x_j \sin w\tau - \dot{x}_j / w \cos w\tau, \\ u_{3j} &=& y_j \cos w\tau - \dot{y}_j / w \sin w\tau, \\ u_{4j} &=& -y_j \sin w\tau - \dot{y}_j / w \cos w\tau \end{array}$$

where 
$$w_0 = \sqrt{k/m}$$
 and  $\tau = w_0 t$ .

# Averaging $\frac{du}{d\tau} = \varepsilon G(u, \tau) \qquad \xrightarrow{\int_0^T} \qquad \frac{du}{d\tau} = \varepsilon \overline{G}(u)$

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#### Amplitude Equations

$$\begin{split} \dot{A}_{j} &= \frac{\varepsilon}{2w} \left[ -\rho A_{j} + \frac{3}{4} \mu |A_{j}|^{2} A_{j} i + w \gamma B_{j} - A_{d} i - \lambda (A_{j+1} - 2A_{j} + A_{j-1}) i \right] \\ \dot{B}_{j} &= \frac{\varepsilon}{2w} \left[ -\rho B_{j} + \frac{3}{4} \mu |B_{j}|^{2} B_{j} i - w \gamma A_{j} \right]. \end{split}$$

where  $\rho = cw_0w + \Delta i$ ,  $\varepsilon \Delta = w^2 - 1$ ,  $\varepsilon = 1/(mw_0^2)$ .

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Modeling General Approach Symmetry Approach

#### Definitions

Symmetry Set of transformations that leave an object unchanged.

Invariance  $f : \mathbf{C}^3 \to \mathbf{R}$  is invariant under a group  $\Gamma$  if  $f(\gamma x) = f(x)$ , for all  $\gamma \in \Gamma$ .

Equivariance  $\frac{dx}{dt} = f(x, \lambda), x \in \mathbb{R}^n$ , has  $\Gamma$ -symmetry if  $f(\gamma x, \lambda) = \gamma f(x, \lambda)$ , for all  $\gamma \in \Gamma$ , where  $\Gamma \subset O(r)$ 

**Isotropy Subgroup** The amount of symmetry of a solution x is given by:  $\Sigma_x = \{\gamma \in \Gamma : \gamma x = x\}.$ 

Fixed Subspace Fix( $\Sigma$ ) = { $x \in \mathbb{R}^n$  :  $\sigma x = x, \forall \sigma \in \Sigma$ }.

Invariance  $f : Fix(\Sigma) \rightarrow Fix(\Sigma)$ 

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#### Let

- $z = (z_d, z_s, A_d)$  be the state-variable of a single gyroscope, where  $z_d = A$  and  $z_s = B$ .
- **2**  $\Gamma \times T^1$  be the group of symmetries of the network.
- **3**  $T^1$  act on  $\mathbf{C}^3$  in the standard way:

$$\theta \dot{z} = (e^{i\theta}z_d, e^{i\theta}z_s, e^{i\theta}A_d).$$

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#### Theorem

(a) A Hilbert basis for the  $T^1$ -invariant polynomials on  $\mathbf{C}^3$  is:  $u_1 = z_d \overline{z}_d, \quad u_2 = z_s \overline{z}_s, \quad u_3 = A_d A_d,$  $V_1 = Z_d \bar{Z}_s, \ \bar{V}_1, \quad V_2 = Z_d \bar{A}_d, \ \bar{V}_2, \quad V_3 = Z_s \bar{A}_d, \ \bar{V}_3.$ (b) The  $T^1$ -equivariant are generated by Sac

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Normal Forms

$$\frac{dz}{dt} = (g_1(z, A_d), g_2(z, A_d), 0),$$

where  $g_1 = p_1 z_d + p_2 z_s + p_3 A_d$ ,  $g_2 = q_1 z_d + q_2 z_s + q_3 A_d$ ,  $p'_i s$  and  $q'_i s$  are complex-valued functions of  $u_1$ ,  $u_2$ ,  $u_3$ ,  $v_1$ ,  $v_2$ ,  $v_3$ .

#### **Network Dynamics**

$$\begin{split} \dot{z}_{dj} &= g_1(z_{dj}, z_{sj}, A_d) + \begin{array}{l} h(z_{d,j+1} - z_{dj}, z_{dj} - z_{d,j-1}) + \\ h(z_{s,j+1} - z_{sj}, z_{sj} - z_{s,j-1}) \\ \dot{z}_{sj} &= g_2(z_{dj}, z_{sj}, A_d) + \begin{array}{l} h(z_{d,j+1} - z_{dj}, z_{dj} - z_{d,j-1}) + \\ h(z_{s,j+1} - z_{sj}, z_{sj} - z_{s,j-1}) \\ \dot{A}_d &= 0. \end{split}$$

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#### **Global Symmetries**

Let  $\gamma \in \Gamma$ . It can be shown that

$$\gamma \cdot (\mathbf{Z}_1, \ldots, \mathbf{Z}_n) = (\mathbf{Z}_{\gamma^{-1}(1)}, \ldots, \mathbf{Z}_{\gamma^{-1}(n)}).$$

Combining local and global symmetries:

$$(\zeta, e^{i\theta})(z_1, \ldots, z_n) = (e^{i\theta} z_{\zeta(1)}, \ldots, e^{i\theta} z_{\zeta(n)}), \quad \text{where } \zeta \in \mathbf{D}_n.$$

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### Predictions

Isotropy subgroup Σ	Fixed-Point Subspace
	Solution
$\mathbf{D}_m(k) = \langle \{\sigma^k, k\}  angle$	In Phase
$\mathbf{D}_m(k\sigma) = \langle \{\sigma^k, k\sigma\}  angle$	In Phase
$\mathbf{Z}_m = \langle \{\sigma^k\}  angle$	In Phase
$\mathbf{D}_m(+-) = \langle \{\sigma^{k-1}k, 1\}, (k\sigma, -1)\} \rangle$ for <i>m</i> even	Standing Wave
$\mathbf{D}_m() = \langle \{\sigma^{k-1}k, 1\}, (k\sigma, -1)\} \rangle$ for k even	Standing Wave
$Z_m(p) = \langle \{\sigma^k, w^{pk}\} \rangle$ where $p \in \{1, \dots, [m/2]\}$	Traveling Wave

Table: Predictions for a  $D_n$ -symmetric CINS network.

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#### Lattice of ISotropy Subgroups



Figure: Lattice of isotropy groups and patterns of oscillation for a CINS ring with  $D_n$ -symmetry, case study n = 3.

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#### One-Parameter Bifurcation



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#### **Applications of Nonlinear Dynamics**

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This edited book is aimed at interdisciplinary device-oriented applications of nonlinear science theory and methods in complex systems. In particular, applications directed to nonlinear phenomena with space and time characteristics. Examples include: complex networks of magnetic sensor systems, coupled nano-mechanical oscillators, nanodetectors, microscale devices, stochastic resonance in multi-dimensional chaotic systems, biosensors, and stochastic signal quantization. "Applications of nonlinear dynamics: model and design of complex systems" brings together the work of scientists and engineers that are applying ideas and methods from nonlinear dynamics to design and fabricate complex systems... more on <u>http://pringer.com/978-3-540-85631-3</u>

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#### Research and Graduate Programs in Nonlinear Dynamics @ SDSU http://nlds.sdsu.edu

#### PhD in Dynamical Systems and Chaos through Comp. Sci.

MS in Dynamical Systems and Chaos through Applied Math



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