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# Boundary Noise in the Chua Circuit

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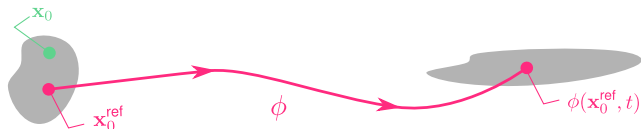
# Linearisation



Suppose the system

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}); \quad \mathbf{x} = \mathbf{x}_0; \quad \text{has the unique solution} \quad \mathbf{x}(t) = \phi(\mathbf{x}_0; t); \quad (1)$$

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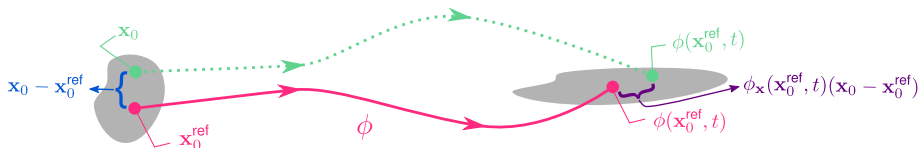


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$$\mathbf{x}(\mathbf{x}_0; t) - \mathbf{x}(\mathbf{x}_0^{\text{ref}}; t) = \mathbf{f}_{\mathbf{x}}(\mathbf{x}_0^{\text{ref}}; t)(\mathbf{x}_0 - \mathbf{x}_0^{\text{ref}}) + O(\|\mathbf{x}_0 - \mathbf{x}_0^{\text{ref}}\|^2); \quad (2)$$

where the Jacobian  $\mathbf{f}_{\mathbf{x}}(\mathbf{x}_0^{\text{ref}}; t)$  is the solution to the IVP

$$\dot{\mathbf{J}} = \mathbf{f}_{\mathbf{x}}(\mathbf{x}_0^{\text{ref}}; t) \mathbf{J}; \quad \mathbf{J}(0) = \mathbf{I}; \quad (3)$$

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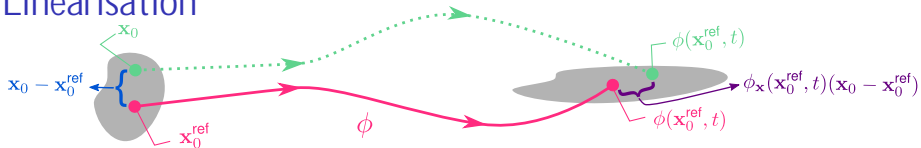


Figure: Linearisation of smooth dynamical systems

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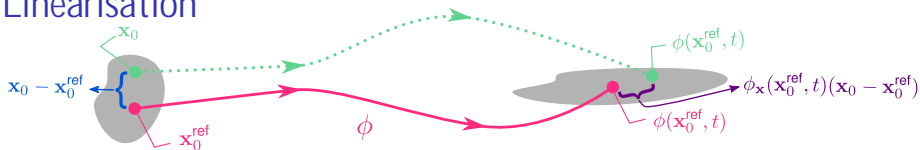


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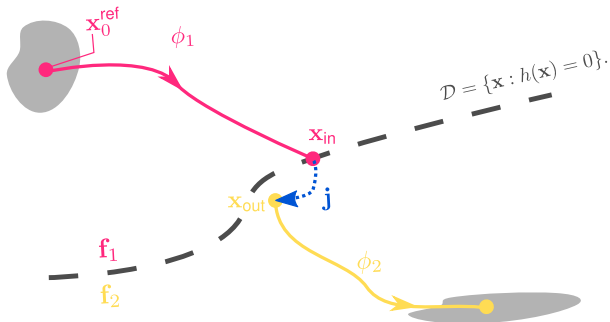


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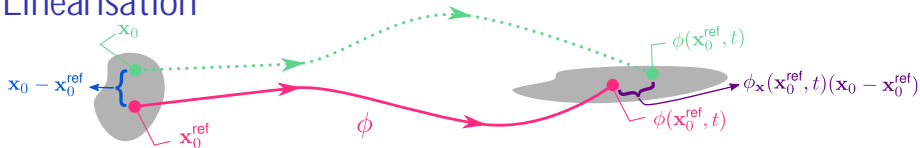


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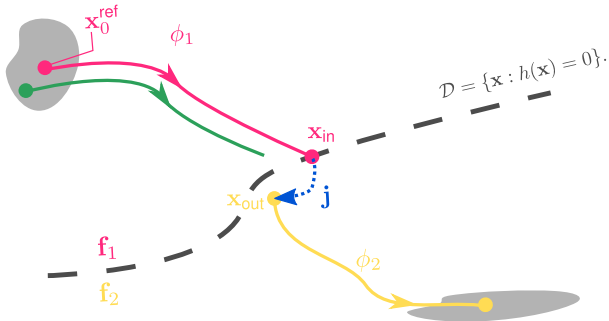


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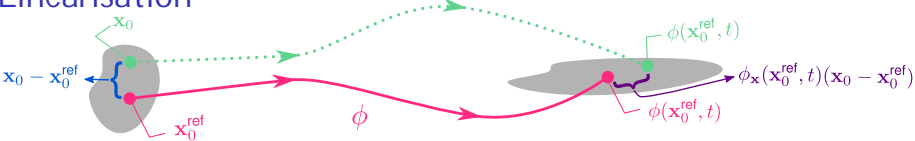


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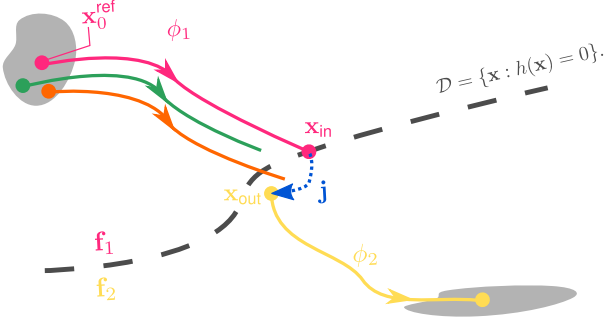


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# Constructing the Zero-Time Discontinuity Mapping

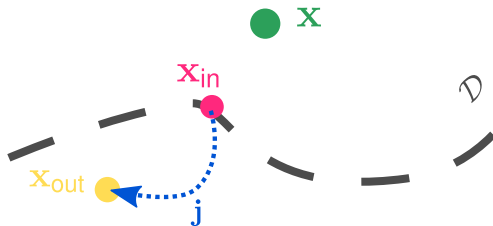


Figure: Constructing the ZDM

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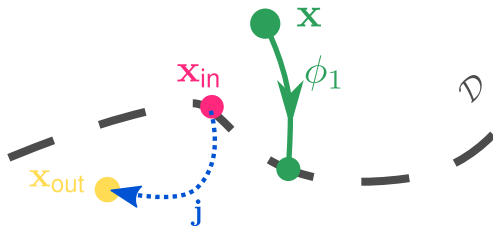


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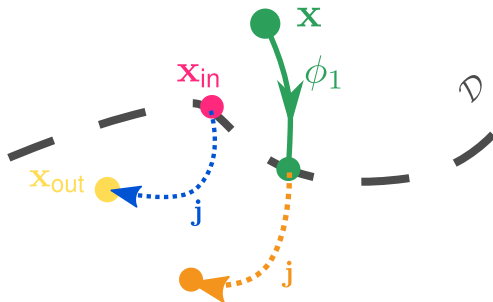


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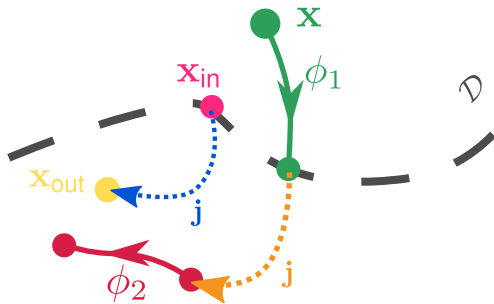


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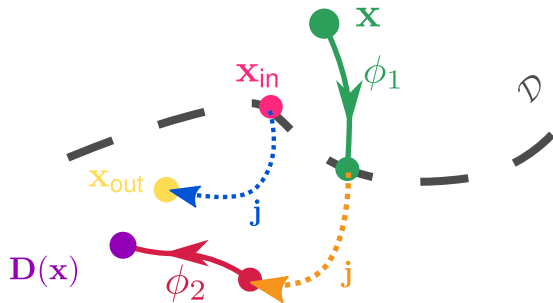


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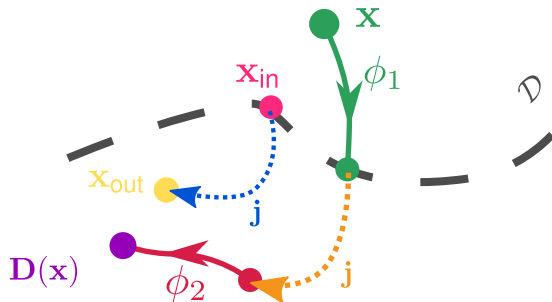


Figure: Constructing the ZDM

We can now write

$$(\mathbf{x}_0; T) = \mathcal{D}(\mathcal{J}(\mathbf{x}_0; t_{\text{ref}}); T, t_{\text{ref}}); \quad (4)$$

where the ZDM

$$\mathcal{D}(\mathbf{x}) = \mathcal{J}(\mathbf{x}; t(\mathbf{x})); \quad t(\mathbf{x}) \quad (5)$$

takes a point in a neighbourhood of  $\mathbf{x}_{\text{in}}$  and maps it to a point in a neighbourhood of  $\mathbf{x}_{\text{out}}$ .

# The Saltation Matrix

The Jacobian of  $\mathbf{D}$  evaluated at  $\mathbf{x}_{\text{in}}$  is given by

$$\begin{aligned}\mathbf{D}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) &= \mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) + (\mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \mathbf{f}_{\text{out}}) t_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \\ &= \mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) + \frac{(\mathbf{f}_{\text{out}} \mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \mathbf{f}_{\text{in}}) h_{\mathbf{x}}(\mathbf{x}_{\text{in}})}{h_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \mathbf{f}_{\text{in}}};\end{aligned}\quad (6)$$

where  $\mathbf{f}_{\text{in}} = \mathbf{f}_1(\mathbf{x}_{\text{in}})$  and  $\mathbf{f}_{\text{out}} = \mathbf{f}_2(\mathbf{x}_{\text{out}})$ . In the case where  $h$  is explicitly time-dependent this becomes

$$\mathbf{D}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) = \mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) + \frac{(\mathbf{f}_{\text{out}} \mathbf{j}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \mathbf{f}_{\text{in}}) h_{\mathbf{x}}(\mathbf{x}_{\text{in}}; t_{\text{ref}})}{h_t(\mathbf{x}_{\text{in}}; t_{\text{ref}}) + h_{\mathbf{x}}(\mathbf{x}_{\text{in}}; t_{\text{ref}}) \mathbf{f}_{\text{in}}};\quad (7)$$

In both cases we have that

$$\mathbf{x}(\mathbf{x}_0^{\text{ref}}; T) = \mathbf{2}; \mathbf{x}(\mathbf{x}_{\text{out}}; T \quad t_{\text{ref}}) \mathbf{D}_{\mathbf{x}}(\mathbf{x}_{\text{in}}) \mathbf{1}; \mathbf{x}(\mathbf{x}_{\text{in}}; t_{\text{ref}}); \quad (8)$$



## Introducing Noise

As in the deterministic case, we define the discontinuity boundary  $D$  as the zeros of a function  $h$ . For a stochastically oscillating boundary we let  $h$  take the form

$$h(\mathbf{x}; t) = \hat{h}(\mathbf{x}; t) P(t); \quad (9)$$

where the function  $\hat{h}$  is deterministic and  $P(t)$  is a stochastic process.

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Let  $\hat{t}_{\text{ref}}$  be the time of flight from  $\mathbf{x}_0^{\text{ref}}$  to the boundary in the absence of noise, i.e.

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We define  $t_{\text{ref}}$  to be the random variable given by the difference between  $\hat{t}_{\text{ref}}$  and the actual time of flight

$$t_{\text{ref}} = \hat{t}_{\text{ref}} - t_{\text{ref}}; \quad (11)$$

## Stochastic Saltation

In order to deal with stochastically oscillating boundaries we extend the state space, such that the state vector and vector field are given by

$$\mathbf{x} = (\mathbf{x}; t; t_{\text{ref}})^T \quad \text{and} \quad \mathbf{f} = (\mathbf{f}; 1; 0)^T; \quad (12)$$

respectively.

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We calculate the saltation matrix in this extended state space before projecting back. As a result, in the original state space we find that

$$(\mathbf{x}_0; t) = (\hat{\mathbf{x}}_0^{\text{ref}}; \hat{t}) \quad \mathbf{x}(\hat{\mathbf{x}}_0^{\text{ref}}; \hat{t}) (\mathbf{x}_0 \quad \hat{\mathbf{x}}_0^{\text{ref}}) + \mathbf{2}; \mathbf{x}(\hat{\mathbf{x}}_{\text{out}}; \hat{t} \quad \hat{t}_{\text{ref}}) (\hat{\mathbf{f}}_{\text{in}} \quad \hat{\mathbf{f}}_{\text{out}}) \quad \hat{t}_{\text{ref}}; \quad (13)$$

where

$$\mathbf{x}(\hat{\mathbf{x}}_0^{\text{ref}}; \hat{t}) = \mathbf{2}; \mathbf{x}(\hat{\mathbf{x}}_{\text{out}}; \hat{t} \quad \hat{t}_{\text{ref}}) \mathbf{D}_{\mathbf{x}}(\hat{\mathbf{x}}_{\text{in}}) \mathbf{1}; \mathbf{x}(\hat{\mathbf{x}}_{\text{in}}; \hat{t}_{\text{ref}}) \quad (14)$$

and

$$\mathbf{D}_{\mathbf{x}}(\hat{\mathbf{x}}_{\text{in}}) = \mathbf{I} + \frac{(\hat{\mathbf{f}}_{\text{out}} \quad \hat{\mathbf{f}}_{\text{in}}) \hat{\mathbf{h}}_{\mathbf{x}}(\hat{\mathbf{x}}_{\text{in}}; \hat{t}_{\text{ref}})}{\hat{\mathbf{h}}_{\mathbf{x}}(\hat{\mathbf{x}}_{\text{in}}; \hat{t}_{\text{ref}}) \hat{\mathbf{f}}_{\text{in}} + \hat{\mathbf{h}}_t(\hat{\mathbf{x}}_{\text{in}}; \hat{t}_{\text{ref}}) \quad V(\hat{t}_{\text{ref}}/P(\hat{t}_{\text{ref}}) = 0)}. \quad (15)$$

In all the above  $\hat{\cdot}$  indicates the values associated with the deterministic reference trajectory.

# Summary

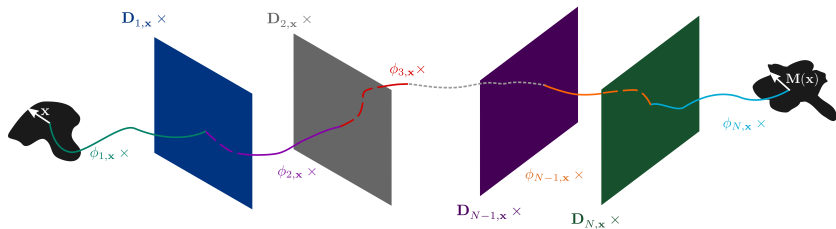


Figure: Linearising Discontinuous Systems

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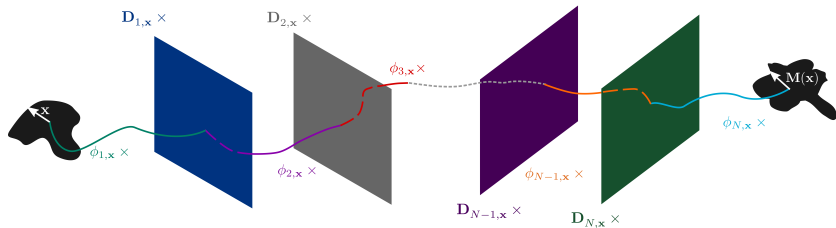
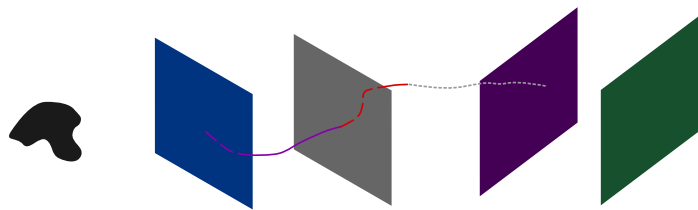


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Easily and cheaply constructed using standard electronic components [Ken92].

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## System equations

The dynamics of the Chua circuit can be described by the following nondimensionalised state equations

$$\begin{aligned}\frac{dx}{dt} &= (y - x - g(x)); \\ \frac{dy}{dt} &= x - y + z; \\ \frac{dz}{dt} &= -(y + z); \end{aligned} \tag{16}$$

where  $g(x)$  is the piecewise linear function representing the characteristic of Chua's diode

$$g(x) = \begin{cases} m_1 x + m_0 & \text{if } x < -1; \\ (m_0 - m_1)x & \text{if } |x| \leq 1; \\ m_1 x + m_0 & \text{if } x > 1; \end{cases} \tag{17}$$

# Complicated Dynamics

Figure: A Zoo of Attractors Produced by the Chua Circuit [BP08]



# Hidden and Self-Excited Attractors

Hidden attractors: have basins of attraction that do not intersect with small neighborhoods of equilibria.

Self-excited attractors : Can be found by following trajectories from the neighbourhoods of unstable equilibria until the end of a transient process [LK13].

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For a range of parameter values the Chua circuit has a 5-stable regime including 3 hidden periodic attractors.

## A Discontinuous Model

Provided the magnitude of  $\epsilon$  is not too large the hidden attractors in the 5-stable regime continue to exist and can be easily found by numerical continuation.

They are destroyed in saddle-bifurcations if the magnitude of  $\epsilon$  grows too large.

**Figure:** Bifurcation diagram showing the saddle bifurcations of  $\epsilon$  as the magnitude of  $\epsilon$  grows. Here  $\mu = 8:4$ ,  $\nu = 12$ ,  $\delta = 0:005$ ,  $m_0 = 1:2$  and  $m_1 = 0:145$ .

# Steady-State Distributions

**Figure:** Steady state distribution of orbit errors on the discontinuity boundary  $\mathcal{D}$  for trajectories with initial condition on the periodic orbit  $C$ .

**Figure:** Convergence of  $z$  to its steady state value for the distribution shown on the left.

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The two periodic attractors merge in a supercritical pitchfork bifurcation if the magnitude grows too large.



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It remains to generalise our method

- Second order terms for continuous systems

- Non-identity boundary mappings

- Dealing with non-transversal intersections

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