

Petri T. Pilroinen
22ND MAY 2019


## Linearisation



Suppose the system

$$
\begin{equation*}
\dot{\mathbf{x}}=\mathbf{f}(\mathbf{x}), \quad \mathbf{x}=\mathbf{x}_{0}, \quad \text { has the unique solution } \quad \mathbf{x}(t)=\phi\left(\mathbf{x}_{0}, t\right) \tag{1}
\end{equation*}
$$

## Linearisation



Suppose the system

$$
\begin{equation*}
\dot{\mathbf{x}}=\mathbf{f}(\mathbf{x}), \quad \mathbf{x}=\mathbf{x}_{0}, \quad \text { has the unique solution } \quad \mathbf{x}(t)=\phi\left(\mathbf{x}_{0}, t\right) \tag{1}
\end{equation*}
$$

Then for $\mathbf{x}_{0}$ in a small neighbourhood of $\mathbf{x}_{0}^{\text {ref }}$

## Linearisation



Suppose the system

$$
\begin{equation*}
\dot{\mathbf{x}}=\mathbf{f}(\mathbf{x}), \quad \mathbf{x}=\mathbf{x}_{0}, \quad \text { has the unique solution } \quad \mathbf{x}(t)=\phi\left(\mathbf{x}_{0}, t\right) \tag{1}
\end{equation*}
$$

Then for $\mathbf{x}_{0}$ in a small neighbourhood of $\mathbf{x}_{0}^{\text {ref }}$

## Linearisation



Suppose the system

$$
\begin{equation*}
\dot{\mathbf{x}}=\mathbf{f}(\mathbf{x}), \quad \mathbf{x}=\mathbf{x}_{0}, \quad \text { has the unique solution } \quad \mathbf{x}(t)=\phi\left(\mathbf{x}_{0}, t\right) \tag{1}
\end{equation*}
$$

Then for $\mathbf{x}_{0}$ in a small neighbourhood of $\mathbf{x}_{0}^{\text {ref }}$

$$
\begin{equation*}
\phi\left(\mathbf{x}_{0}, t\right)-\phi\left(\mathbf{x}_{0}^{\text {ref }}, t\right)=\phi_{\mathbf{x}}\left(\mathbf{x}_{0}^{\text {ref }}, t\right)\left(\mathbf{x}_{0}-\mathbf{x}_{0}^{\text {ref }}\right)+\mathcal{O}\left(\left\|\mathbf{x}_{0}-\mathbf{x}_{0}^{\text {ref }}\right\|\right) \tag{2}
\end{equation*}
$$

where the Jacobian $\phi_{\mathbf{x}}\left(\mathbf{x}_{0}^{\text {ref }}, t\right)$ is the solution to the IVP

$$
\begin{equation*}
\dot{\mathbf{\Phi}}=\mathbf{f}_{\mathbf{x}}\left(\phi\left(\mathbf{x}_{0}^{\text {ref }}, t\right)\right) \mathbf{\Phi}, \quad \boldsymbol{\Phi}(0)=\mathbf{I} . \tag{3}
\end{equation*}
$$

## Linearisation



Figure: Linearisation of smooth dynamical systems

## Linearisation



Figure: Linearisation of smooth dynamical systems


Figure: A nonsmooth dynamical system

## Linearisation



Figure: Linearisation of smooth dynamical systems


Figure: A nonsmooth dynamical system

## Linearisation



Figure: Linearisation of smooth dynamical systems


Figure: A nonsmooth dynamical system

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM

## Constructing the Zero-Time Discontinuity Mapping



Figure: Constructing the ZDM
We can now write

$$
\begin{equation*}
\phi\left(\mathbf{x}_{0}, T\right)=\phi_{2}\left(\mathbf{D}\left(\phi_{1}\left(\mathbf{x}_{0}, t_{\mathrm{ref}}\right)\right), T-t_{\mathrm{ref}}\right), \tag{4}
\end{equation*}
$$

where the ZDM

$$
\begin{equation*}
\mathbf{D}(\mathbf{x})=\phi_{2}\left(\mathbf{j}\left(\phi_{1}(\mathbf{x}, t(\mathbf{x}))\right),-t(\mathbf{x})\right) \tag{5}
\end{equation*}
$$

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 $\mathbf{x}_{\mathrm{in}}$ is given by

$$
\begin{align*}
\mathbf{D}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right) & =\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)+\left(\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)-\mathbf{f}_{\text {out }}\right) t_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right) \\
& =\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)+\frac{\left(\mathbf{f}_{\text {out }}-\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right) \mathbf{f}_{\text {in }}\right) h_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)}{h_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right) \mathbf{f}_{\text {in }}} \tag{6}
\end{align*}
$$

where $\mathbf{f}_{\text {in }}=\mathbf{f}_{1}\left(\mathbf{x}_{\text {in }}\right)$ and $\mathbf{f}_{\text {out }}=\mathbf{f}_{2}\left(\mathbf{x}_{\text {out }}\right)$. In the case where $h$ is explicitly time-dependent this becomes

$$
\begin{equation*}
\mathbf{D}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)=\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right)+\frac{\left(\mathbf{f}_{\text {out }}-\mathbf{j}_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}\right) \mathbf{f}_{\text {in }}\right) h_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}, t_{\text {ref }}\right)}{h_{t}\left(\mathbf{x}_{\text {in }}, t_{\text {ref }}\right)+h_{\mathbf{x}}\left(\mathbf{x}_{\text {in }}, t_{\text {ref }}\right) \mathbf{f}_{\text {in }}} . \tag{7}
\end{equation*}
$$

In both cases we have that

$$
\begin{equation*}
\phi_{\mathbf{x}}\left(\mathbf{x}_{0}^{\mathrm{ref}}, T\right)=\phi_{2, \mathbf{x}}\left(\mathbf{x}_{\mathrm{out}}, T-t_{\mathrm{ref}}\right) \mathbf{D}_{\mathbf{x}}\left(\mathbf{x}_{\mathrm{in}}\right) \phi_{1, \mathbf{x}}\left(\mathbf{x}_{\mathrm{in}}, t_{\mathrm{ref}}\right) \tag{8}
\end{equation*}
$$

## Introducing Noise

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

$$
\begin{equation*}
h(\mathbf{x}, t)=\hat{h}(\mathbf{x}, t)-P(t) \tag{9}
\end{equation*}
$$

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

## Introducing Noise

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

$$
\begin{equation*}
h(\mathbf{x}, t)=\hat{h}(\mathbf{x}, t)-P(t), \tag{9}
\end{equation*}
$$

where the function $\hat{h}$ is deterministic and $P(t)$ is a stochastic process. We further require that $P$ is a mean reverting stochastic process that has mean 0 , is at least once differentiable and does not depend on $\mathbf{x}$.

## Introducing Noise

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

$$
\begin{equation*}
h(\mathbf{x}, t)=\hat{h}(\mathbf{x}, t)-P(t) \tag{9}
\end{equation*}
$$

where the function $\hat{h}$ is deterministic and $P(t)$ is a stochastic process. We further require that $P$ is a mean reverting stochastic process that has mean 0 , is at least once differentiable and does not depend on $\mathbf{x}$.

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.

$$
\begin{equation*}
\hat{h}\left(\phi_{1}\left(\mathbf{x}_{0}^{\text {ref }}, \hat{t}_{\mathrm{ref}}\right)\right)=0 \tag{10}
\end{equation*}
$$

## Introducing Noise

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

$$
\begin{equation*}
h(\mathbf{x}, t)=\hat{h}(\mathbf{x}, t)-P(t) \tag{9}
\end{equation*}
$$

where the function $\hat{h}$ is deterministic and $P(t)$ is a stochastic process. We further require that $P$ is a mean reverting stochastic process that has mean 0 , is at least once differentiable and does not depend on $\mathbf{x}$.

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.

$$
\begin{equation*}
\hat{h}\left(\phi_{1}\left(\mathbf{x}_{0}^{\text {ref }}, \hat{t}_{\text {ref }}\right)\right)=0 \tag{10}
\end{equation*}
$$

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

$$
\begin{equation*}
\Delta t_{\mathrm{ref}}=t_{\mathrm{ref}}-\hat{t}_{\mathrm{ref}} . \tag{11}
\end{equation*}
$$

## Stochastic Saltation Matrix

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

$$
\begin{equation*}
\tilde{\mathbf{x}}=\left(\mathbf{x}, t, \Delta t_{\mathrm{ref}}\right)^{T} \quad \text { and } \quad \tilde{\mathbf{f}}=(\mathbf{f}, 1,0)^{T}, \tag{12}
\end{equation*}
$$

respectively.

## Stochastic Saltation Matrix

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

$$
\begin{equation*}
\tilde{\mathbf{x}}=\left(\mathbf{x}, t, \Delta t_{\mathrm{ref}}\right)^{T} \quad \text { and } \quad \tilde{\mathbf{f}}=(\mathbf{f}, 1,0)^{T} \tag{12}
\end{equation*}
$$

respectively.
We calculate the saltation matrix in this extended state space before projecting back. As a result, in the original state space we find that
$\phi\left(\mathbf{x}_{0}, t\right)-\phi\left(\hat{\mathbf{x}}_{0}^{\text {ref }}, t\right) \approx \phi_{\mathbf{x}}\left(\hat{\mathbf{x}}_{0}^{\text {ref }}, t\right)\left(\mathbf{x}_{0}-\hat{\mathbf{x}}_{0}^{\text {ref }}\right)+\phi_{2, \mathbf{x}}\left(\hat{\mathbf{x}}_{\text {out }}, t-\hat{t}_{\text {ref }}\right)\left(\hat{\mathbf{f}}_{\text {in }}-\hat{\mathbf{f}}_{\text {out }}\right) \Delta t_{\text {ref }}$,
where

$$
\begin{equation*}
\phi_{\mathbf{x}}\left(\hat{\mathbf{x}}_{0}^{\text {ref }}, t\right)=\phi_{2, \mathbf{x}}\left(\hat{\mathbf{x}}_{\text {out }}, t-\hat{t}_{\text {ref }}\right) \mathbf{D}_{\mathbf{x}}^{*}\left(\hat{\mathbf{x}}_{\text {in }}\right) \phi_{1, \mathbf{x}}\left(\hat{\mathbf{x}}_{\text {in }}, \hat{t}_{\text {ref }}\right) \tag{13}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathbf{D}_{\mathbf{x}}^{*}\left(\hat{\mathbf{x}}_{\text {in }}\right)=\mathbf{I}+\frac{\left(\hat{\mathbf{f}}_{\text {out }}-\hat{\mathbf{f}}_{\text {in }}\right) \hat{h}_{\mathbf{x}}\left(\hat{\mathbf{x}}_{\text {in }}, \hat{t}_{\text {ref }}\right)}{\hat{h}_{\mathbf{x}}\left(\hat{\mathbf{x}}_{\text {in }}, \hat{t}_{\text {ref }}\right) \hat{\mathbf{f}}_{\text {in }}+\hat{h}_{t}\left(\hat{\mathbf{x}}_{\text {in }}, \hat{t}_{\text {ref }}\right)-V\left(\hat{t}_{\text {ref }} \mid P\left(\hat{t}_{\text {ref }}\right)=0\right)} \tag{15}
\end{equation*}
$$

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

## Summary



Figure: Linearising Discontinuous Systems

## Summary



Figure: Linearising Discontinuous Systems


## The Chua Circuit



Figure: The Chua Circuit


Figure: The $V-I$ characteristic of the Chua Diode.

- Created with the aim of being the simplest autonomous circuit capable of generating chaos [Mat84, Chu92].
- First physical system for which the presence of chaos was shown experimentally, numerically and mathematically [CKM86].
- Contains four linear elements and one nonlinear resistor known as a Chua diode.
- Easily and cheaply constructed using stadard electronic components [Ken92].


## System equations

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

$$
\begin{align*}
\frac{d x}{d t} & =\alpha(y-x-g(x)) \\
\frac{d y}{d t} & =x-y+z \\
\frac{d z}{d t} & =-(\beta y+\gamma z) \tag{16}
\end{align*}
$$

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

$$
g(x)= \begin{cases}m_{1} x+m_{1}-m_{0} & \text { if } x<-1  \tag{17}\\ \left(m_{0}-\epsilon\right) x & \text { if }|x| \leq 1 \\ m_{1} x+m_{0}-m_{1} & \text { if } x>1\end{cases}
$$

## 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].

## 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].



For a range of parameter values the Chua circuit has a 5-stable regime including 3 hidden periodic attractors [SKLC17].

## 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 $\mathbf{C}^{-}$as the magnitude of $\epsilon$ grows. Here $\alpha=8.4, \beta=12, \gamma=-0.005, m_{0}=-1.2$ 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 $\mathbf{C}^{-}$.


Figure: Convergence of $\sigma_{z}$ to its steady state value for the distribution shown on the left.

## Destroying Periodic Attractors

### 0.238



## Destroying Periodic Attractors



## A 3-Stable Regime

For a range of parameter values the Chua circuit has a 3-stable regime including 2 symmetric periodic attractors.



## A 3-Stable Regime

For a range of parameter values the Chua circuit has a 3-stable regime including 2 symmetric periodic attractors.




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

## Merging Periodic Attractors



## Merging Periodic Attractors



Towards Bifurcation

## Conclusions

- The concept of a saltation matrix can be generalised to stochastic systems.


## Conclusions

- The concept of a saltation matrix can be generalised to stochastic systems.
- This can be used to estimate the dynamics of discontinuous systems with noisy boundaries.
- destruction of attractors
- multi/monostability
- merging of attractors
- flickering/switching


## Conclusions

- The concept of a saltation matrix can be generalised to stochastic systems.
- This can be used to estimate the dynamics of discontinuous systems with noisy boundaries.
- destruction of attractors
- multi/monostability
- merging of attractors
- flickering/switching
- It remains to generalise our method
- Higher order terms for continuous systems
- Non-identity boundary mappings
- Dealing with non-transversal intersections
- Rugged, stochastic discontinuity surfaces

Eleonora Bilotta and Pietro Pantano, A gallery of chua attractors, vol. 61, World Scientific, 2008.

- Leon O Chua, The genesis of chua's circuit, International Journal of Electronis Communication 46 (1992), no. 4, 250-257.

E- Leon O Chua, Motomasa Komuro, and Takashi Matsumoto, The double scroll family, IEEE transactions on circuits and systems 33 (1986), no. 11, 1072-1118.

E Mario Di Bernardo, Chris J Budd, Alan R Champneys, Piotr Kowalczyk, Arne B Nordmark, Gerard Olivar Tost, and Petri T Piiroinen, Bifurcations in nonsmooth dynamical systems, SIAM review 50 (2008), no. 4, 629-701.

國 Michael Peter Kennedy, Robust op amp realization of chua's circuit, Frequenz 46 (1992), no. 3-4, 66-80.

围 Gennady A Leonov and Nikolay V Kuznetsov, Hidden attractors in dynamical systems. from hidden oscillations in hilbert-kolmogorov, aizerman, and kalman problems to hidden chaotic attractor in chua circuits, International Journal of Bifurcation and Chaos 23 (2013), no. 01, 1330002.

Takashi Matsumoto, A chaotic attractor from chua's circuit, IEEE Transactions on Circuits and Systems 31 (1984), no. 12, 1055-1058.
目 Nataliya V Stankevich, Nikolay V Kuznetsov, Gennady A Leonov, and Leon O Chua, Scenario of the birth of hidden attractors in the chua circuit, International Journal of Bifurcation and Chaos 27 (2017), no. 12, 1730038.
Eoghan J Staunton and Petri T Piiroinen, Discontinuity mappings for stochastic nonsmooth systems, In Preparation (2019).

R Estimating the dynamics of systems with noisy boundaries, Submitted (2019).

