# Compositionality Results for Cardiac Cell Dynamics 

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## Iyer-Mazhari-Winslow Myocyte Model



Resting
$\downarrow$

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## Iyer-Mazhari-Winslow Myocyte Model



## Fenton-Cherry-Orovio Minimal Model



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## Main Challenge



$$
\dot{\mathbf{V}}=-\left(\mathbf{I}_{\mathrm{Na}}+\mathbf{I}_{\mathrm{Ca}}+\mathbf{I}_{\mathrm{Ca}, \mathrm{~K}}+\mathbf{I}_{\mathrm{Kr}}+\mathbf{I}_{\mathrm{Ks}}+\mathbf{I}_{\mathrm{K} 1}+\mathbf{I}_{\mathrm{Na}, \mathrm{Ca}}+\mathbf{I}_{\mathrm{Na}, \mathrm{~K}}+\mathbf{I}_{\mathrm{to}}+\mathbf{I}_{\mathrm{p}(\mathrm{Ca})}+\mathbf{I}_{\mathrm{Cab}}+\mathbf{I}_{\mathrm{Nab}}+\mathbf{I}_{\mathrm{stim}}\right)
$$

## Main Challenge



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## Outline

## - Problem Statement

- Background
- lyer et al. (IMW) sodium channel component
- Model-order reduction for identifying Hodgkin-Huxley type abstractions
- Compositionality
- Bisimulation Functions
- Input-to-Output Stability (IOS)-based equivalence of dynamical systems
- Small-Gain Theorem for feedback compositionality
- Computing BFs using Sum-of-Squares Optimization
- Results
- Conclusions and Ongoing Work


## Problem Statement

$\Sigma_{1}$ : 13-state voltage-controlled sodium channel Continuous Time Markov Chain (CTMC) subsystem used in the IMW model
$\Sigma_{\mathrm{H}}$ : 2-state abstraction of $\Sigma_{\mathrm{l}}$, identified using curve fitting
$\Sigma_{\mathrm{c}}$ : Capacitor-like context representing the membrane
$\Sigma_{\mathrm{Cl}}, \Sigma_{\mathrm{CH}}$ : Canonical cell models with only the sodium channel subsystem and the membrane composed using feedback


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Are $\Sigma_{\mathrm{C} I}$ and $\Sigma_{\mathrm{CH}}$ equivalent?


$\sum_{\mathrm{CH}}$

## Background: IMW's Sodium Channel Component



- Dynamics: $\dot{\mathbf{x}}_{1}=\mathrm{A}_{1}(\mathrm{~V}) \mathbf{x}_{1}, \mathrm{~A}_{1}(\mathrm{~V}) \in \mathcal{R}^{13} \times \mathcal{R}^{13}$

$$
x_{1}=\left[C_{00}, C_{10}, C_{20}, C_{30}, C_{40}, O_{1}, O_{2}, C_{01}, C_{11}, C_{21}, C_{31}, C_{41}, I\right]^{\top}
$$

- Input: Trans-membrane voltage V
- Output: Channel conductance $o(V)$, which determines $\mathrm{I}_{\mathrm{Na}}$
- Transition rates: Exponential function of V


## Background: Model-Order Reduction for Identifying Hodgkin-Huxley (HH)-Type Abstractions




Published in CMSB'12

## Bisimulation Functions (BFs)

BFs: contractive metrics that characterize IOS-based equivalence of two dynamical systems.

$$
\begin{aligned}
u_{i} \in \mathcal{R}^{m} & \begin{array}{c}
x_{i} \in \mathcal{R}^{n_{i}} \\
\dot{x}_{i} i=f_{i}\left(x_{i}, u_{i}\right)
\end{array} \left\lvert\, \begin{array}{l}
y_{i}=g_{i}\left(x_{i}\right) \\
g_{i}: \mathcal{R}^{n_{i}}
\end{array} \rightarrow \mathcal{R}^{p}\right.
\end{aligned}
$$

$\mathrm{BF} \mathrm{S}\left(\mathrm{x}_{1}, \mathrm{x}_{2}\right): \mathcal{R}^{\mathrm{n}_{1}} \times \mathcal{R}^{\mathrm{n}_{2}} \rightarrow \mathcal{R}_{\geq 0}$ between $\Sigma_{1}$ and $\Sigma_{2}$ is a smooth function such that,

1. $S$ bounds output difference

$$
\left\|g_{1}\left(x_{1}\right)-g_{2}\left(x_{2}\right)\right\| \leq S\left(x_{1}, x_{2}\right)
$$

2. S decays along trajectories

$$
\forall \mathrm{u}_{1}, \mathrm{u}_{2}, \mathrm{x}_{1}, \mathrm{x}_{2}, \exists \lambda>0, \gamma \geq 0 \text { such that }
$$

$$
\frac{\partial S}{\partial x_{1}} f_{1}\left(x_{1}, u_{1}\right)+\frac{\partial S}{\partial x_{2}} f_{2}\left(x_{2}, u_{2}\right) \leq-\lambda S\left(x_{1}, x_{2}\right)+\gamma\left\|u_{1}-u_{2}\right\|
$$

## Theorem 1: BFs Imply IOS

## IOS : Bounded input difference leads to bounded output difference

For all $\mathbf{t} \geq 0$,

$$
\begin{aligned}
\left\|g_{1}\left(x_{1}(t)\right)-g_{2}\left(x_{2}(t)\right)\right\| & \leq S\left(x_{1}(t), x_{2}(t)\right) \\
& \leq e^{-\lambda t} S\left(x_{1}(0), x_{2}(0)\right)+\frac{\gamma}{\lambda}\left\|u_{1}-u_{2}\right\|_{\infty}
\end{aligned}
$$

where $\left\|u_{1}-u_{2}\right\|_{\infty}=\sup _{t \geq 0}\left\|u_{1}(t)-u_{2}(t)\right\|$
i.e. max difference in input signals

## Feedback Composition

BFs can be linearly composed subject to small gain condition (sgc)

$\mathrm{S}_{12}\left(\lambda_{12}, \gamma_{12}\right)$ : BF between $\Sigma_{1}$ and $\Sigma_{2}$ $\Sigma_{13}$ $\mathrm{S}_{3}\left(\lambda_{3}, \gamma_{3}\right)$ : BF between $\Sigma_{3}$ and itself $\quad\left(\alpha_{1}, \alpha_{2}\right)$ chosen as:

$$
\begin{aligned}
& \text { If } \frac{\gamma_{12} \gamma_{3}}{\lambda_{12} \lambda_{3}}<1(\mathrm{sgc}), \\
& \begin{aligned}
\mathrm{S}\left(\left[\mathrm{x}_{1}, \mathrm{x}_{3}\right],\left[\mathrm{x}_{2}, \mathrm{x}_{3}^{\prime}\right]\right) & =\alpha_{1} \mathrm{~S}_{12}\left(\mathrm{x}_{1}, \mathrm{x}_{2}\right) \\
& +\alpha_{2} \mathrm{~S}_{3}\left(\mathrm{x}_{3}, \mathrm{x}_{3}^{\prime}\right)
\end{aligned}
\end{aligned}
$$

where $\mathbf{S}$ is a BF between $\Sigma_{13}$ and $\Sigma_{23}$

## Methodology

Proving equivalence of $\Sigma_{\mathrm{CI}}$ and $\Sigma_{\mathrm{CH}}$


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Proving equivalence of $\Sigma_{\mathrm{CI}}$ and $\Sigma_{\mathrm{CH}}$


Equivalence of $\Sigma_{I}$ and $\Sigma_{\mathrm{H}}$

Sum-of-Square (SoS) polynomials computed using SoS optimization in SOSTOOLS

checking sgc $\checkmark$


IOS property of $\Sigma_{c}$

## Preprocessing of $\Sigma_{I}$ and $\Sigma_{\mathrm{H}}$



## Equivalent Model of $\Sigma_{\mathrm{H}}$

- Output of $\Sigma_{\mathbf{H}}$ is nonlinear
- Higher degree in output leads to higher degree in BF
- Time complexity increases with degree of BF
- $\Sigma_{\mathrm{H}}^{\prime}$ is voltage-controlled counting CTMC with linear output
$\Sigma_{\mathrm{H}}$ : Output: $\mathrm{O}=\mathrm{m}^{3} \mathrm{~h}$ $\dot{\mathrm{m}}=\alpha_{\mathrm{m}}(\mathrm{V})(1-\mathrm{m})-\beta_{\mathrm{m}}(\mathrm{V}) \mathrm{m}$
$\dot{\mathrm{h}}=\alpha_{\mathrm{h}}(\mathrm{V})(1-\mathrm{h})-\beta_{\mathrm{h}}(\mathrm{V}) \mathrm{h}$
Equivalent Model (invariant manifold)
$\Sigma_{\mathrm{H}}^{\prime}$ : Output: 0

$$
\ddot{x}_{H}^{\prime}=A_{H}^{\prime}(V) x_{H}^{\prime}, A_{H}^{\prime}(V) \in \mathcal{R}^{8} \times \mathcal{R}^{8}
$$

$$
\mathbf{x}_{H}^{\prime}=\left[\mathrm{C}_{00}, \mathrm{C}_{10}, \mathrm{C}_{20}, \mathrm{O}, \mathrm{C}_{01}, \mathrm{C}_{11}, \mathrm{C}_{21}, \mathrm{C}_{31}\right]^{\top}
$$



## SoS Optimization Problem

- SoS Polynomial:

A multivariate polynomial function $p\left(x_{1}, x_{2}, \ldots, x_{n}\right)=p(x)$ is an SoS polynomial if there exists $f_{1}(x), f_{2}(x), \ldots, f_{m}(x)$ such that

$$
p(x)=\sum_{i=1}^{m} f_{1}^{2}(x)=c_{1} w_{1} x_{1}^{n}+c_{2} w_{2} x_{1}^{n-1} x_{2}+L
$$

- SoS Optimization Problem(SOSP):
$\min _{c} c^{\top} w$
such that
$p_{i}(x)$ is an SoS for $i=1,2, \ldots, n$
where $\mathbf{C}=\left[\mathbf{C}_{1}, \mathbf{C}_{2}, \ldots, \mathbf{C}_{n}\right]^{\boldsymbol{T}}, \mathbf{C}_{\mathbf{i}}$ is co-efficient vector of $\mathbf{p}_{\mathbf{i}}(\mathbf{x})$, for $\mathbf{i}=1,2, \ldots, \mathbf{n}$, and $\mathbf{w}$ is some given weight vector.
- SOSTOOLS:

A Matlab toolbox to solve SoS optimization problem.

## Formulation of SOSPs for $S_{I H}$ and $S_{C}$

$\mathrm{P}_{\mathrm{IH}}$ : SOSP to compute $\mathrm{S}_{\mathrm{IH}}$
$\min _{\mathrm{C}} \mathrm{C}^{\top} \mathbf{w}$

## such that

$P_{I H}: \quad S_{I H}\left(x_{I}, x_{H}\right)-\left(g_{1}\left(x_{I}\right)-g_{H}\left(x_{H}\right)\right)^{2}$ is SoS
$-\left(\frac{\partial S}{\partial x_{I}} A_{1}^{\prime}\left(V_{I}\right)+\frac{\partial S}{\partial x_{H}} A_{H}^{\prime \prime}\left(V_{H}\right)\right)-\lambda_{I H} S\left(x_{1}, x_{H}\right)$
$+\gamma_{1 H}\left\|V_{1}-V_{H}\right\|$ is SoS for all $\left(V_{I}, V_{H}\right)$
$\mathbf{P}_{\mathrm{C}}$ : SOSP to compute $\mathrm{S}_{\mathrm{c}}$
$\min _{C} C^{\top} w$
such that
$S_{c}\left(x_{c}, x_{c}^{\prime}\right)-\left(g_{c}\left(x_{c}\right)-g_{c}\left(x_{c}^{\prime}\right)\right)^{2}$ is SoS
$-\left(\frac{\partial S}{\partial x_{c}}\left(G_{N a}\left(x_{c}-V_{N a}\right) O_{1}\right)+\frac{\partial S}{\partial x_{c}^{\prime}}\left(G_{N a}\left(x_{c}^{\prime}-V_{N a}\right) O_{H}\right)\right)-$
$\lambda_{c} S_{c}\left(x_{C}, x_{c}^{\prime}\right)+\gamma_{C} \mid O_{1}-O_{H} \|$ is SoS for all $\left(O_{1}, O_{H}\right)$

## Choosing Form of BFs

- First step to compute BFs in SOSTOOLS is to choose form of BFs.
- Ellipsoidal polynomial (sosvar in SOSTOOLS) form is chosen for BFs:

$$
\mathbf{S}\left(\mathbf{x}_{1}, \mathbf{x}_{2}\right)=\mathbf{z}^{\top} \mathbf{Q} \mathbf{z}
$$

where $\mathbf{z}=\left[\mathbf{x}_{1} ; \mathbf{x}_{2}\right], \mathbf{x}_{\mathbf{i}}$, for $\mathbf{i}=\mathbf{1 , 2}$, is a state vector of $\boldsymbol{\Sigma}_{\mathbf{i}}$ and $\mathbf{Q}$ is a positive semi-definitve matrix which contains the decision variables of SOSP.

- pvar toolbox is used to define polynomial variable in SOSTOOLS.


## Input Space Quantization

- Second condition of BF needs to be held for all pairs of inputs.
- SOSTOOLS can not handle continuous input space.
- BFS are computed using quantized input space in SOSTOOLS.


Continuous bounded input space $\mathcal{U}$


Quantized input space $\mathcal{U}^{\text {d }}$

## Input Space Quantization Contd.

- Quantization of Input space can be justified by sensitivity analysis.
- Overall bound on output differences computed by BF due to input space quantization: $\delta_{1}+\delta_{2}+\delta_{3}$.



## Choosing Optimization Functions

- BF bounds outputput differences.
- Choosing a proper objective function is critical to obtain a tight bounds on output differences.
- Theorem 1 implicates BF is maximum at initial states.
- Minimizing BF at initial states provides better bound.


Fig. $\mathbf{S}_{\mathbf{H}}$ plotted along a pair of trajectories of $\Sigma_{1}$ and $\Sigma_{\mathrm{H}}$. Objective function-1: minimizes BF at all states. Objective function-2: minimizes BF only at initial states.

## Handling $\lambda$ and $\gamma$

- Fixed value is used for $\lambda$
- Fixed value is used for $\gamma$
- Criteria for choosing $\lambda$ and $\gamma: \frac{\gamma_{1 H} \gamma_{C}}{\lambda_{1 H} \lambda_{C}}<1$ (sgc)

| Problem | BF | $\lambda$ | $\gamma$ |
| :---: | :---: | :---: | :---: |
| $P_{I H}$ | $S_{I H}$ | $\lambda_{I H}=\mathbf{0 . 1}$ | $\gamma_{I H}=\mathbf{0 . 0 0 1}$ |
| $P_{C}$ | $S_{C}$ | $\lambda_{C}=\mathbf{0 . 0 1}$ | $\gamma_{C}=\mathbf{0 . 0 0 0 1}$ |

Table: Fixed values for $\lambda$ and $\gamma$

## Results: <br> BF between Two Sodium Channels

## $S_{I H}=\left[x_{1} ; x_{H}\right]^{\top} Q\left[x_{I} ; x_{H}\right]$

 where $\mathbf{x}_{\mathrm{I}} \in \mathcal{R}_{\geq 0}^{12}, \mathbf{x}_{\mathrm{H}} \in \mathcal{R}_{\geq 0}^{7}$ and $\mathbf{Q} \in \mathcal{R}^{19} \times \mathcal{R}^{19}$ is a positive semidefinitive matrix


$\mathrm{V}_{\mathrm{I}}(\mathrm{t})=-30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(\mathrm{t})=-\mathbf{3 0 m V}$
$V_{1}(t)=-30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(\mathrm{t})=30 \mathrm{mV}$
$\mathrm{V}_{\mathrm{I}}(\mathrm{t})=30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(\mathrm{t})=-30 \mathrm{mV}$
Fig. $\mathbf{S}_{\mathrm{IH}}$ covers output differences and decays along two trajectories of $\Sigma_{I}$ and $\Sigma_{\mathrm{H}}$. Three pairs of trajectories are generated using three different pairs of input signals.

## Results: <br> BF for Context

$$
\mathrm{S}_{\mathrm{c}}=1.27 \mathrm{~V}_{\mathrm{l}}^{2}-1.4599 \mathrm{~V}_{\mathrm{V}} \mathrm{~V}_{\mathrm{H}}+1.27 \mathrm{~V}_{\mathrm{H}}^{2}
$$



Fig. $\mathbf{S}_{\mathrm{c}}$ covers output differences and decays along two trajectories of $\Sigma_{\mathrm{c}}$. Three pairs of trajectories are generated using three different pairs of input signals.

## Results:

## BF between Two Composed Systems

$$
\begin{aligned}
& S=\alpha_{1} S_{I H}+\alpha_{2} S_{C} \\
& \left(\alpha_{1}, \alpha_{2}\right)=(1,1)
\end{aligned}
$$

$$
\begin{aligned}
\lambda & =\min \left(\frac{\alpha_{1} \lambda_{\mathrm{IH}}-\alpha_{2} \gamma_{\mathrm{C}}}{\alpha_{1}}, \frac{\alpha_{2} \gamma_{\mathrm{C}}-\alpha_{1} \lambda_{\mathrm{IH}}}{\alpha_{2}}\right) \\
& =0.009
\end{aligned}
$$


$\mathrm{V}_{1}(0)=-30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(0)=-30 \mathrm{mV}$

$\mathrm{V}_{\mathrm{I}}(0)=-30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(0)=30 \mathrm{mV}$

$\mathrm{V}_{\mathrm{I}}(0)=30 \mathrm{mV}, \mathrm{V}_{\mathrm{H}}(0)=-30 \mathrm{mV}$

Fig. S covers output differences and decays along two trajectories of $\Sigma_{\mathrm{Cl}}$ and $\Sigma_{\text {ch }}$. Three pairs of trajectories are generated using three different pairs of input signals.

## Results: <br> 3D Visualization of BFs



Fig. All three BFs cover the the corresponding output differences and are non-increasing at all time. BFs are plotted along the crossproduct of a pair of trajectories of the corresponding systems.

## Results:

## Empirical Evidence of Compositionality



Conductances Comparison


Fig. Simulation of two composed systems $\Sigma_{\mathrm{CI}}$ and $\Sigma_{\mathrm{CH}}$. Substituition of $\Sigma_{1}$ by $\Sigma_{\mathrm{H}}$ tends to accumultae error, but existence of BF between them ensures that the error is bounded. The mean L1 error: Conductances: $\mathbf{9 \times 1 0 ^ { - 3 }}$, Voltage: $\mathbf{1 . 4 2 m V}$

## Ongoing Work

- Applying abstraction and compositional reasoning to other ionic, pump and exchanger currents on IMW model
- More effective ways of covering input spaces
- Finding a better covering of output differences
- Restricting the domain of BFs
- Formalization of applying scaling functions on SOSTOOLS-based BFs
- Non-dimensionalization of context for more reasonable composed BF


Fig. Application of exponential scaling function on $\mathbf{S}_{\mathbf{I H}}$

## Conclusions

- Cast IMW cardiac cell model as a feedback composition of sodium channel and rest of the model
- Identified approximately bisimilar 2-state HH-type abstraction for 13 -state sodium channel model of IMW using curve fitting-based procedure (PEFT+RFI)
- Identified BFs using Sum-of-Square relaxation in SOSTOOLS
- Verifying small-gain theorem for cardiac cell model
- Compositionality results for cardiac cell dynamics based on BFs

