U.S. FOOD & DRUG ADMINISTRATION

Generative Modeling for Hardware-in-the-Loop Testing of Fluid Resuscitation Control Algorithms

Ali Tivay[1,2], Ramin Bighamian[2], Jin-Oh Hahn[1], Christopher G. Scully[2]

[1]Department of Mechanical Engineering, University of Maryland
[2]Office of Science and Engineering Laboratories, Center for Devices and Radiological Health, U.S. Food and Drug Administration

Background and Objective

- Model-based testing of a physiologic closed-loop control algorithm can be performed completely computationally (in-silico) or with hardware-in-the-loop (HIL) methods (e.g., with the physical devices).
- While HIL methods provide additional realism, they are more time-consuming than computational approaches
- We investigated a generative modeling approach to efficient sample virtual populations for inclusion in HIL testing and compare against in-silico results

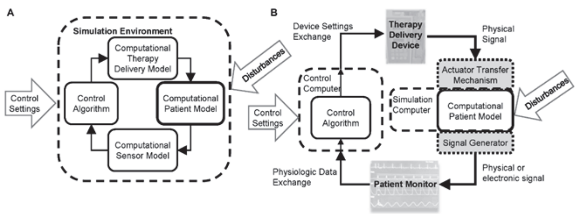


*Figure: Parvinian, Bahram, et al. "Credibility evidence for computational patient models used in the development of physiological closed-loop controlled devices for critical care medicine." *Frontiers in physiology* 10 (2019): 220. (CC)

Generative Physiological Modeling

- **Generative model:** a probabilistic model that aims to reproduce the patterns and variabilities present in data:

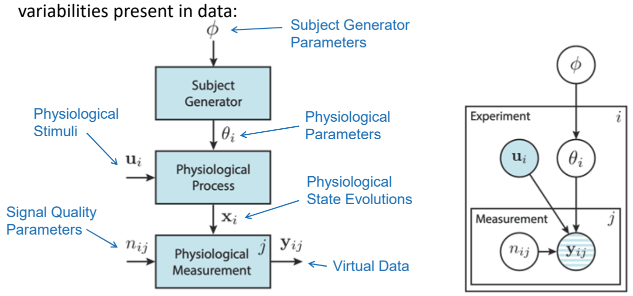
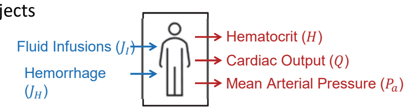
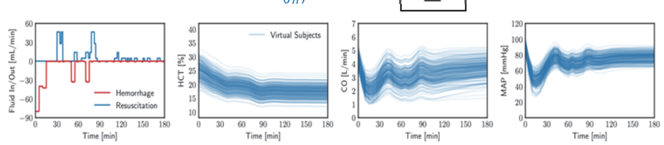


*Figure: Tivay, Ali et al. "Collective variational inference for personalized and generative physiological modeling: A case study on hemorrhage resuscitation." *IEEE Transactions on Biomedical Engineering* 69, no. 2 (2022): 666-677. © 2022 IEEE

- Application to hemodynamic modeling in fluid resuscitation:
  - N = 23 animal (sheep) subjects
  - Hemorrhage
  - Crystalloid infusions



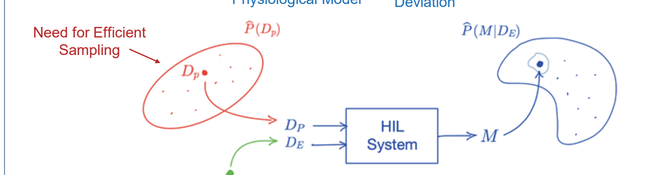


Generative Algorithm Testing

- Generative modeling was used to generate "virtual patients", test the algorithm against these virtual patients, and calculate algorithm performance measures

$$\hat{P}(M|D_E) = \mathbb{E}_{D_P\sim\hat{P}(D_P)}[P(M|D_P, D_E)]$$

Measure (e.g., Control Performance)
Generative Physiological Model
Patient-Related Deviation
Equipment-Related Deviation



- Generative modeling provides an efficient sampling approach to identify a small number of virtual patients that are representative of the population:

Unscented Transformation Sampling

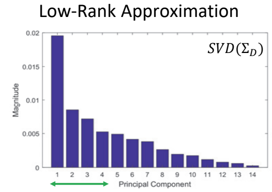
$D_0 = \mu_D$ ← Generator Mean → 1 sample

$D_{1:n} = \mu_D + (n+\kappa)\sqrt{\Sigma_D}$ → n samples

$D_{n+1:2n} = \mu_D - (n+\kappa)\sqrt{\Sigma_D}$ → n samples

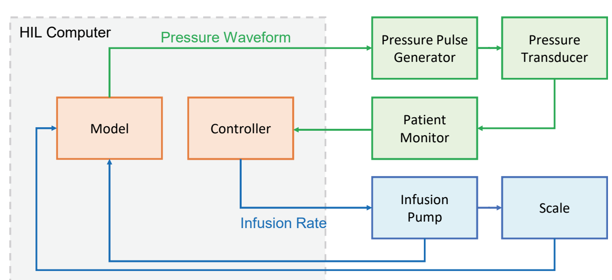
Number of Parameters; Tuning Parameter; Generator Covariance

Low-Rank Approximation



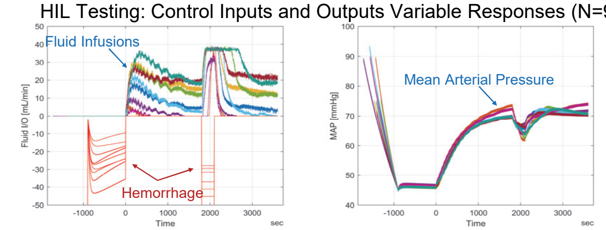
Hardware-in-the-loop Testing Setup

Virtual patients with the same fluid loss disturbance profiles were evaluated in a purely computational (in-silico) setup and hardware-in-the-loop setup.

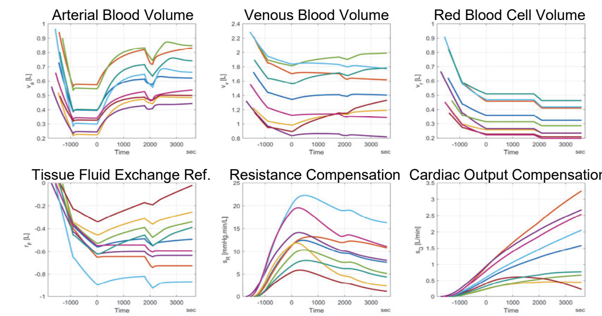


Results and Discussion

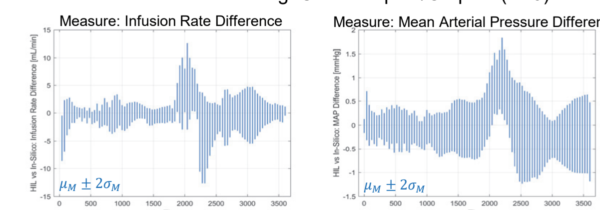
HIL Testing: Control Inputs and Outputs Variable Responses (N=9)



HIL Testing: Internal Variable Responses (N=9)



HIL vs In-Silico Testing: Control Inputs/Outputs (N=9)



Conclusion

Generative modeling showed promise in facilitating the in-silico and HIL testing of a 2DOF-PID-based fluid resuscitation control algorithm.

Comparing in-silico and HIL testing results may provide useful information to identify limitations of in-silico approaches

Funding: NSF INTERN Grant #1760817 and NSF CAREER Grant #1748762.