

Sub-Millisecond Construction of Digital Twin Using AI

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Introduction

High-rate systems

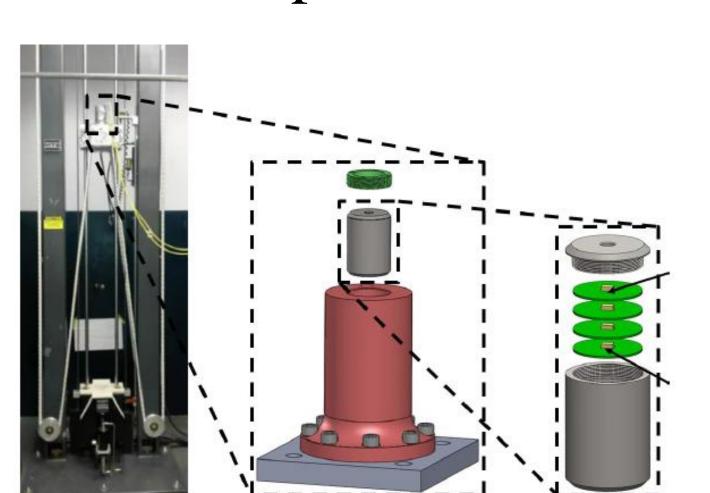
- Experiencing accelerations higher than $100 g_n$ in less than 1 ms
- Large uncertainties in the external loads
- High levels of non-stationarities
- Generation of unmodeled dynamics

High-rate structural health monitoring challenges

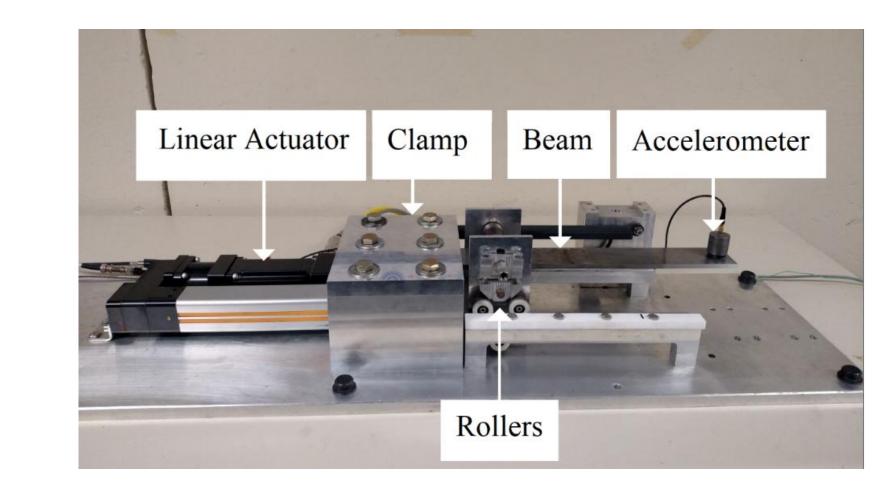
- Unknown or uncertain dynamics
- Real-time modeling requirement
- Less than 100 µs computation time per decision step
- Limited access to training data

High-rate laboratory datasets

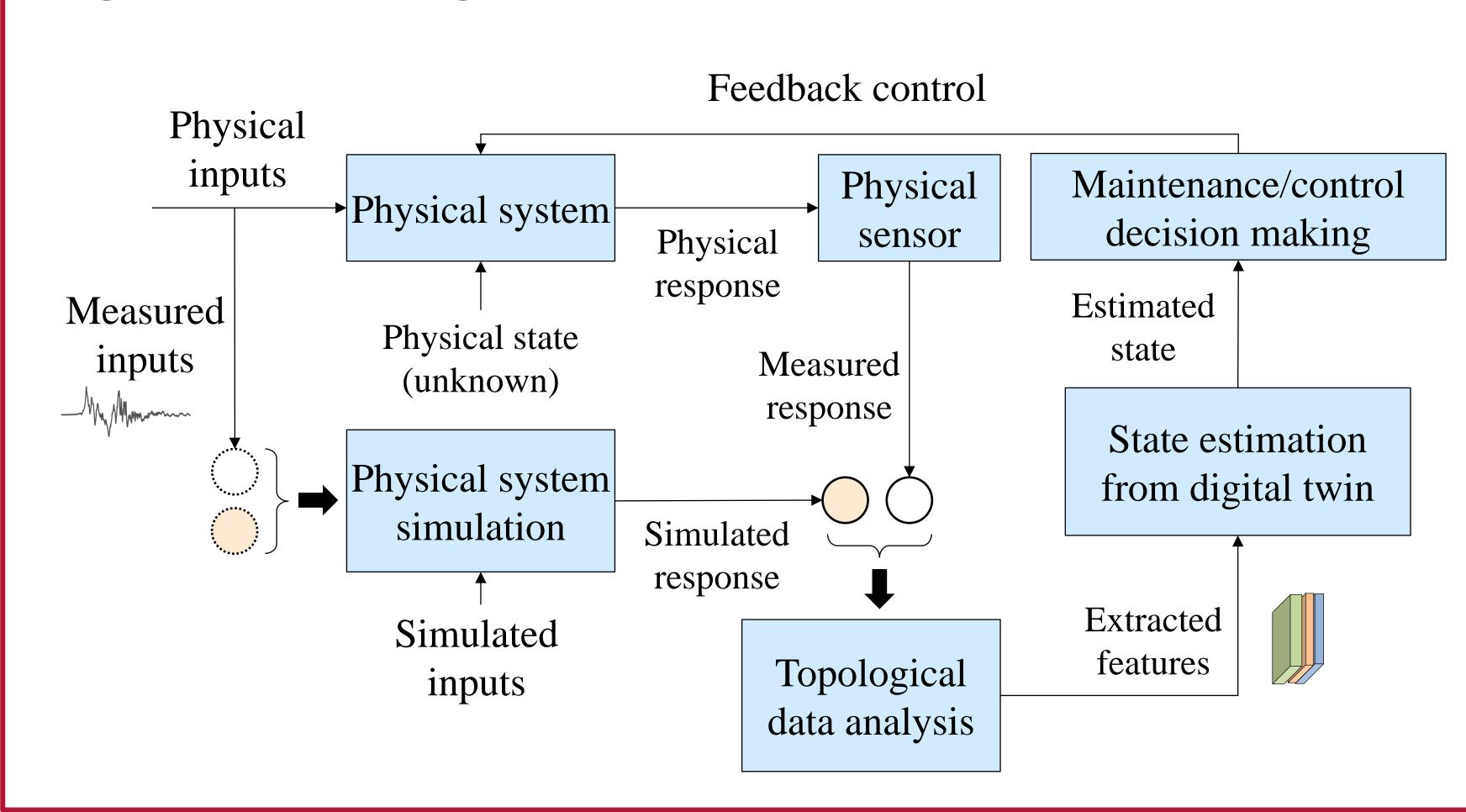
Drop tower



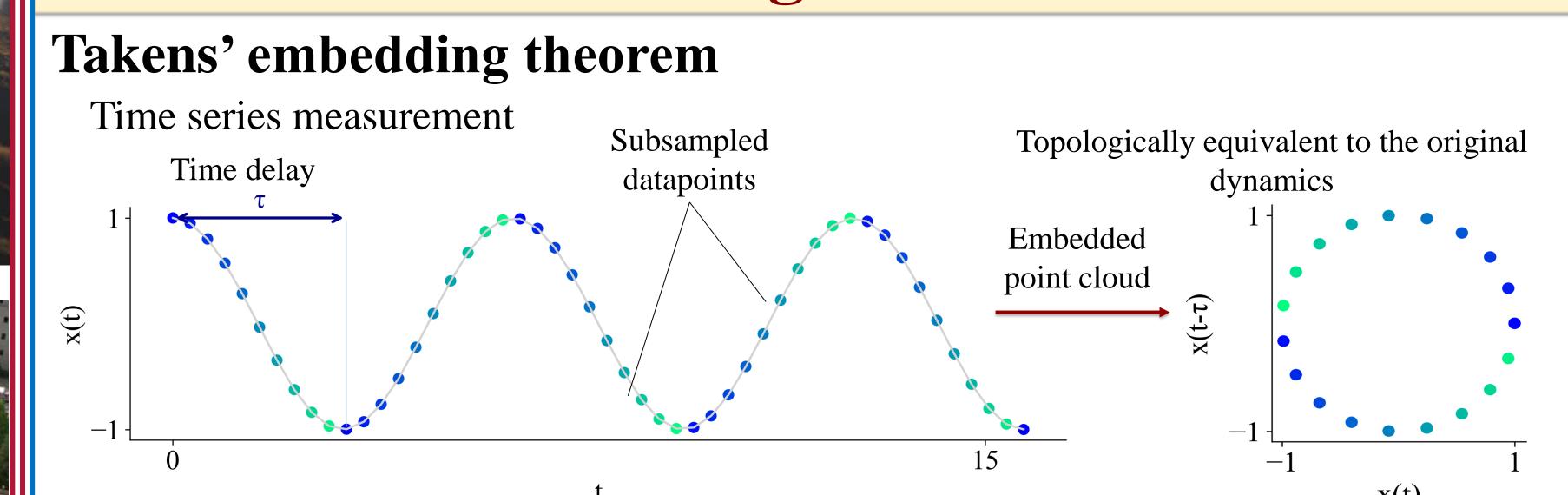
DROPBEAR



Digital twin for high-rate state estimation



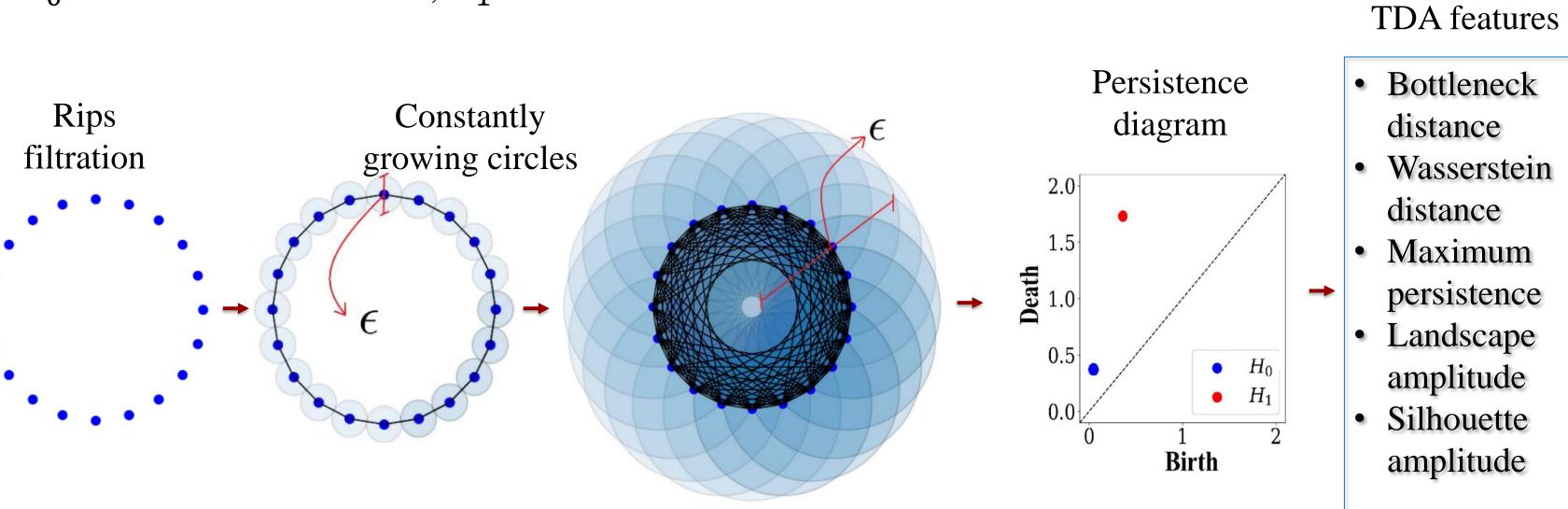
Methodology



Background

Persistent homology

- Employing simplicial complex on embedded point cloud to compute homology groups
- Keep a record of various ε values
- H_0 zero-dimensional hole, H_1 one-dimensional hole



Algorithm TDA Time series Multi-resolution Real-time state parameters measurement sliding window selection estimation Data pre-processing Dimension Low pass filtration Time delay Normalization Window Sub-millisecond digital twin TDA feature extraction Pseudo-structure Gaussian process regression Neural network ensemble (NNE) Monte Carlo dropout Recurrent neural network (RNN) + **NNE** RNN + MCAccuracy and uncertainty Trained state Probabilistic quantification prediction estimator Ground truth

Results

Model performance metrics

Model	MAE (mm)	TRAC	NLL	ECE (%)	Computation time per sample (ms)
NN	6.856	0.991	-	-	26.896
RNN	5.901	0.994	-	-	26.961
GPR	6.508	0.991	-2.339	10.625	27.107
MC Dropout	8.475	0.990	3.282	22.264	26.932
NNE	6.309	0.992	-4.304	13.621	27.220
RNN-MC	7.524	0.992	-2.613	16.001	27.156
RNN-NNE	5.030	0.995	-2.498	7.817	27.158

Parameters for TDA feature extraction

Parameter	Value (unit)	
H_0 Window size	0.1 (s)	
H_1 Window size	0.1333(s)	
Time delay (τ)	0.0083 (s)	
Embedding dimension (d)	3	
Window step size	1 (step)	

References

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