Literature Review: Machine Learning Applied to Dynamic Physial System

I. Abstract

II. Background

A. Modeling of physical systems

1) Traditional work in modeling physical systems
   Automated Design of Complex Dynamic Systems [1]

2) Data driven design
   Theory-Guided Data Science: A New Paradigmfor Scientific Discovery from Data [2]

   a) Machine learning based approach
      Data-Driven Discovery of Governing Physical Laws and Their Parameteric Dependencies in Engineering, Physics and Biology [3]
      Data-driven discovery of partial differential equations [4]
      Discovering governing equations from data: Sparse identification of nonlinear dynamical systems [5]

   b) Deep learning based approach
      Towards a Hybrid Approach to Physical ProcessModeling
      Deep learning for universal linear embeddings of nonlinear dynamics [6]
      Nonlinear Systems Identification Using Deep Dynamic Neural Networks [7]
      Analyzing Inverse Problems withInvertible Neural Networks [8]
      Deep Hidden Physics Models: Deep Learning ofNonlinear Partial Differential Equations [9]
      How Can Physics Inform Deep Learning Methods inScientific Problems?: Recent Progress andFuture Prospects
      Learning New Physics from a Machine [10]
      Nanophotonic Particle Simulation and Inverse DesignUsing Artificial Neural Networks
      Particle Track Reconstruction with Deep Learning
      Neural Message Passing for Jet Physics
      Physics-guided Neural Networks (PGNN):An Application in Lake Temperature Modeling [11]

   c) Reinforcement learning based approach
      Large-Scale Study of Curiosity-Driven Learning [12]
      DeepMimic: Example-Guided Deep Reinforcement Learningof Physics-Based Character Skills [**?**]

   d) Adversarial learning based approach
      Tips and Tricks for Training GANs with PhysicsConstraints
      Adversarial learning to eliminate systematic errors:a case study in High Energy Physics

B. Solving PDEs

Solving differential equations with unknownconstitutive relations as recurrent neural networks

C. Non-linear control

Adaptive Inverse Control of Linear and Nonlinear Systems Using Dynamic Neural Networks [13]
Nonlinear System Control Using Neural Networks
Feedback-Linearization-Based Neural Adaptive Control for Unknown Nonaffine Nonlinear Discrete-Time Systems
A Novel Neural Approximate Inverse Control for Unknown Nonlinear Discrete Dynamical Systems [14]
Intelligent Control Using Neural Networks and Multiple Models [15]
Dynamic Power Conditioning Method of Microgrid Via Adaptive Inverse Control [16]
Discrete-time neuroadaptive control using dynamic state feedback with application to vehicle motion control for intelligent vehicle highway systems [17]
Identification and Adaptive Control of Dynamic Nonlinear Systems Using Sigmoid Diagonal Recurrent Neural Network [18]

D. Motor control

E. Time series

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