Literature Review: Machine Learning Applied to Dynamic Physial System

I. Abstract

This survery is on recent advancements in the intersection of physical modelling and machine learning.

II. Introduction

Understanding of physical process from data when there is no first prinicple solution is very hard. The abundance of data in both natural and physical sciences has enabled the use of machine learning models to understand governing dynamics of many complex processes. There are different ways in which physical modeling and machine learning methods have been used together. There are works in the problem of understanding pysical process from data, classifying or predicting complex physical process, using physics to generate simulation data, using machine learning to control non-linear dynamical systems, using machine learning to do fault detection in dynamical systems, etc.

This survey is on all the different areas where there has been an amalgation of machine learning and physics. The application on which we focus is on time series modeling, non-linear control, motor control, and fault detection.

III. Background

The background section is divided in to the following subsections; first is modeling of physical systems, second is on non-linear control, third is on motor control, and fourth is on fault detection.

A. Modeling of physical systems

This section is on recent works where modeling of dynamical systems using machine learning has been done. Modeling of complex systems has been presented in [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?]

HMM or Kalman filter are able to learn linear dynamic models, for non-linear dynamics accomodating nonlinearity into HMM is very hard. In [?] a new method called sufficient posterior representation is presented which can be used to model nonlinear dynamic behaviors using many nonlinear supervised learning algorithms such as neural networks, boosting and SVM in a simple and unified fashion.

PDEs can describe complex phoenomena. We don't always have PDEs for a given problem, but we may have a large amount of data available. In [?] a data driven method is proposed to learn governing PDEs of a given system from time series data. Sparse regression is used to learn the coefficients and an iterative method is used to get most suitable coefficients. Experiments on Navier-Stokes equation is shown.

In [?] modeling of time invariant nonlinear systems is addressed. A multi-layered network architecture with a control input signal called Hidden Control Neural Network (HCNN) is presented which can model signals generated by nonlinear dynamical systems with restricted time variability.

Reinforcement learning has also been used for physial modelling. In [?] a Temporal Difference learning algorithm for continuous-time, continuous-state, nonlinear control problems is presented. Kernel regression method is used to learn a nonlinear auto-regressive model.

[?] uses machine learning to optimize physical dynamic systems.

Most of the methods of data driven learning of dynamic systems deal with sequential data. In [?] method is presented to learn dynamics from non-sequential data.

Computing hidden system paramters from measurable quantities of complex physical systems using invertible neural network(INN) is presented in [?].

In [?] a deep learning appraoch for discovering nonlinear partial differential equations from scattered and potentially noisy observations is presented. Two deep neural networks are used to approximate solution and nonlinear dynamics.

In [?] a data driven approach of approximating nonlinear dynamics to a linear one using deep neural networks has been present. Koopman operators are learned from data for coordinate transformation of nonlinear system to linear one.

In [?], [?] a physics-guided neural networ(PGNN) is presented which leverages the output of physics-based model simulations along with observational features to generate predictions using a neural network. The model predictions not only show lower errors on the training data but are also consistent with the system dynamics.

There are systems where dynamics change with time and some dynamics may not have been seen before. It will be usefull to identify new dynamics. [?] uses neural networks to identify new phsyics.

[?] have trained three deep neural network structures on sequential data and have shown detailed analysis on how DNNs are able to model the underlying dynamical systems.

[?] has shown how physics can be used to do better data driven discoveries. Theory guided design, learning, refinement of machine learning model has been presented.

In [?] a multi-layered neural networks called Hidden Control Neural Network(HCNN) is presented to model nonlinear dynamical systems with restricted time variability. The mapping of NN changes with time as a function of an aditional control input signal.

B. Nonlinear Control

[?], [?]

Using recurrent network to create mixture of expertes for modelling and controlling dynamical systems is presented in [?].

IN [?] a dynamical system is first modeled using recurrent neural network(RNN). Then the dynamic response of the system is controlled using another RNN. Disturbance cancelling is performed using an adtitional RNN.

In [?] a recurrent neural network architecture called Simoid Diagonal Recurrent Neural Network(SDRNN) is used for adaptive control of nonlinear dynamical systems.

In [?] a feedforward neural network is used to control an unkown stochastic nonlinear dynamical system.

In [?] recurrent neural network is used to control nonlinear plants. Approach is used in controlin landing of a commercial aircraft in difficult wind conditions.

In []

C. Motor Control

[?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?], [?]

D. Fault Detection

[?], [?], [?], [?], [?], [?], [?], [?], [?], [?]

REFERENCES

[1] J. Langford, R. Salakhutdinov, and T. Zhang, "Learning nonlinear dynamic models," in *Proceedings of the 26th Annual International Conference on Machine Learning*, ser. ICML '09. New York, NY, USA: ACM, 2009, pp. 593–600. [Online]. Available: http://doi.acm.org/10.1145/1553374.1553451

[2] S. H. Rudy, S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Data-driven discovery of partial differential equations," *Science Advances*, vol. 3, no. 4, p. e1602614, 2017. [Online]. Available: http://dx.doi.org/10.1126/sciadv.1602614

[3] E. Levin, "Modeling time varying systems using hidden control neural architecture," in *Advances in Neural Information Processing Systems 3*, R. P. Lippmann, J. E. Moody, and D. S. Touretzky, Eds. Morgan-Kaufmann, 1991, pp. 147–154. [Online]. Available: http://papers.nips.cc/paper/363-modeling-time-varying-systems-using-hidden-control-neural-architecture.pdf

[4] K. Doya, "Temporal difference learning in continuous time and space," in *Advances in Neural Information Processing Systems 8*, D. S. Touretzky, M. C. Mozer, and M. E. Hasselmo, Eds. MIT Press, 1996, pp. 1073–1079. [Online]. Available: http://papers.nips.cc/paper/1169-temporal-difference-learning-in-continuous-time-and-space.pdf

[5] M. Hermans, B. Schrauwen, P. Bienstman, and J. Dambre, "Automated design of complex dynamic systems," *PLoS ONE*, vol. 9, no. 1, p. e86696, 2014. [Online]. Available: http://dx.doi.org/10.1371/journal.pone.0086696

[6] L. Ardizzone, J. Kruse, S. Wirkert, D. Rahner, E. W. Pellegrini, R. S. Klessen, L. Maier-Hein, C. Rother, and U. Kthe, "Analyzing inverse problems with invertible neural networks," 2018. [Online]. Available: http://arxiv.org/abs/1808.04730

[7] M. Raissi, "Deep hidden physics models: Deep learning of nonlinear partial differential equations," 2018. [Online]. Available: http://arxiv.org/abs/1801.06637

[8] B. Lusch, J. N. Kutz, and S. L. Brunton, "Deep learning for universal linear embeddings of nonlinear dynamics," 2017. [Online]. Available: http://arxiv.org/abs/1712.09707

[9] E. d. Bezenac, A. Pajot, and P. Gallinari, "Towards a hybrid approach to physical process modeling," *Deep Learning for Physical Sciences workshop in Neural Information Processing Systems*, 2017. [Online]. Available: https://dl4physicalsciences.github.io/files/nips_dlps_2017_9.pdf

[10] R. T. D'Agnolo and A. Wulzer, "Learning new physics from a machine," 2018. [Online]. Available: http://arxiv.org/abs/1806.02350

[11] O. Ogunmolu, X. Gu, S. Jiang, and N. Gans, "Nonlinear systems identification using deep dynamic neural networks," 2016. [Online]. Available: http://arxiv.org/abs/1610.01439

[12] A. Karpatne, W. Watkins, J. Read, and V. Kumar, "Physics-guided neural networks (pgnn): An application in lake temperature modeling," 2017. [Online]. Available: http://arxiv.org/abs/1710.11431

[13] A. Karpatne, G. Atluri, J. H. Faghmous, M. Steinbach, A. Banerjee, A. Ganguly, S. Shekhar, N. Samatova, and V. Kumar, "Theory-guided data science: A new paradigm for scientific discovery from data," *IEEE Transactions on Knowledge and Data Engineering*, vol. 29, no. 10, pp. 2318–2331, 2017. [Online]. Available: http://dx.doi.org/10.1109/tkde.2017.2720168

[14] T. W. Cacciatore and S. J. Nowlan, "Mixtures of controllers for jump linear and non-linear plants," in *Advances in Neural Information Processing Systems 6*, J. D. Cowan, G. Tesauro, and J. Alspector, Eds. Morgan-Kaufmann, 1994, pp. 719–726. [Online]. Available: http://papers.nips.cc/paper/750-mixtures-of-controllers-for-jump-linear-and-non-linear-plants.pdf

[15] G. L. Plett, "Adaptive inverse control of linear and nonlinear systems using dynamic neural networks," *IEEE Transactions on Neural Networks*, vol. 14, no. 2, pp. 360–376, March 2003.

[16] T. Aboueldahab and M. Fakhreldin, "Identification and adaptive control of dynamic nonlinear systems using sigmoid diagonal recurrent neural network," *Intelligent Control and Automation*, vol. 02, no. 03, pp. 176–181, 2011. [Online]. Available: http://dx.doi.org/10.4236/ica.2011.23021

[17] R. A. Milito, I. Guyon, and S. A. Solla, "Neural network implementation of admission control," in *Advances in Neural Information Processing Systems 3*, R. P. Lippmann, J. E. Moody, and D. S. Touretzky, Eds. Morgan-Kaufmann, 1991, pp. 493–499. [Online]. Available: http://papers.nips.cc/paper/327-neural-network-implementation-of-admission-control.pdf

[18] C. Schley, Y. Chauvin, V. Henkle, and R. Golden, "Neural networks structured for control application to aircraft landing," in *Advances in Neural Information Processing Systems 3*, R. P. Lippmann, J. E. Moody, and D. S. Touretzky, Eds. Morgan-Kaufmann, 1991, pp. 415–421. [Online]. Available: http://papers.nips.cc/paper/384-neural-networks-structured-for-control-application-to-aircraft-landing.pdf

[19] G. M. Scott, J. W. Shavlik, and W. H. Ray, "Refining pid controllers using neural networks," in *Advances in Neural Information Processing Systems 4*, J. E. Moody, S. J. Hanson, and R. P. Lippmann, Eds. Morgan-Kaufmann, 1992, pp. 555–562. [Online]. Available: http://papers.nips.cc/paper/503-refining-pid-controllers-using-neural-networks.pdf

[20] E. Hansen, A. G. Barto, and S. Zilberstein, "Reinforcement learning for mixed open-loop and closed-loop control," in *Proceedings of the Ninth Neural Information Processing Systems Conference*, Denver, Colorado, 1996, pp. 1026–1032. [Online]. Available: http://rbr.cs.umass.edu/shlomo/papers/HBZnips96.html

[21] T. Kuremoto, M. Obayashi, and K. Kobayashi, "Nonlinear prediction by reinforcement learning," in *Advances in Intelligent Computing*, D.-S. Huang, X.-P. Zhang, and G.-B. Huang, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 1085–1094.

[22] S. Gadaleta and G. Dangelmayr, "Optimal chaos control through reinforcement learning," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 9, no. 3, pp. 775–788, 1999.

[23] S. Levine, Z. Popovic, and V. Koltun, "Nonlinear inverse reinforcement learning with gaussian processes," in *Advances in Neural Information Processing Systems 24*, J. Shawe-Taylor, R. S. Zemel, P. L. Bartlett, F. Pereira, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2011, pp. 19–27. [Online]. Available: http://papers.nips.cc/paper/4420-nonlinear-inverse-reinforcement-learning-with-gaussian-processes.pdf

[24] J. G. Schneider, "Exploiting model uncertainity estimates for safe dynamic control learning," in *Proceedings of the Tenth Neural Information Processing Systems Conference*, 1997.

[25] K. Doya, "Efficient nonlinear control with actor-tutor architecture," in *Advances in Neural Information Processing Systems 9*, M. C. Mozer, M. I. Jordan, and T. Petsche, Eds. MIT Press, 1997, pp. 1012–1018. [Online]. Available: http://papers.nips.cc/paper/1228-efficient-nonlinear-control-with-actor-tutor-architecture.pdf

[26] K. Rawlik, M. Toussaint, and S. Vijayakumar, "An approximate inference approach to temporal optimization in optimal control," in *Advances in Neural Information Processing Systems 23*, J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor, R. S. Zemel, and A. Culotta, Eds. Curran Associates, Inc., 2010, pp. 2011–2019. [Online]. Available: http://papers.nips.cc/paper/4018-an-approximate-inference-approach-to-temporal-optimization-in-optimal-control.pdf

[27] E. Todorov, "Compositionality of optimal control laws," in *Proceedings of the 22Nd International Conference on Neural Information Processing Systems*, ser. NIPS'09. USA: Curran Associates Inc., 2009, pp. 1856–1864. [Online]. Available: http://dl.acm.org/citation.cfm?id=2984093.2984301

[28] P. Li, X. Wang, W.-J. Lee, and D. Xu, "Dynamic power conditioning method of microgrid via adaptive inverse control," *IEEE Transactions on Power Delivery*, vol. 30, no. 2, pp. 906–913, 2015. [Online]. Available: http://dx.doi.org/10.1109/tpwrd.2014.2323083

[29] M. Watter, J. T. Springenberg, J. Boedecker, and M. A. Riedmiller, "Embed to control: A locally linear latent dynamics model for control from raw images," *CoRR*, vol. abs/1506.07365, 2015. [Online]. Available: http://arxiv.org/abs/1506.07365

[30] M. I. Jordan and R. A. Jacobs, "Learning to control an unstable system with forward modeling," in *Advances in Neural Information Processing Systems 2*, D. S. Touretzky, Ed. Morgan-Kaufmann, 1990, pp. 324–331. [Online]. Available: http://papers.nips.cc/paper/199-learning-to-control-an-unstable-system-with-forward-modeling.pdf

[31] I. Rivals and L. Personnaz, "Nonlinear Internal Model Control using Neural networks : application to Processes with Delay and Design Issues," *IEEE Transactions on Neural Networks*, vol. 11, no. 1, pp. 80–90, 2000. [Online]. Available: https://hal-espci.archives-ouvertes.fr/hal-00797666

[32] L. J. Brown, G. E. Gonye, and J. S. Schwaber, "Non-linear pi control inspired by biological control systems," in *Proceedings of the 37th IEEE Conference on Decision and Control (Cat. No.98CH36171)*, vol. 1, Dec 1998, pp. 1040–1045 vol.1.

[33] A. K. Susemihl, R. Meir, and M. Opper, "Optimal neural codes for control and estimation," in *Advances in Neural Information Processing Systems 27*, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 2987–2995. [Online]. Available: http://papers.nips.cc/paper/5390-optimal-neural-codes-for-control-and-estimation.pdf

[34] M. C. Mozer, L. Vidmar, and R. H. Dodier, "The neurothermostat: Predictive optimal control of residential heating systems," in *NIPS*, 1996.

[35] H. Deng, H. Li, and Y. Wu, "Feedback-linearization-based neural adaptive control for unknown nonaffine nonlinear discrete-time systems," *IEEE Transactions on Neural Networks*, vol. 19, no. 9, pp. 1615–1625, Sept 2008.

[36] L. Chen and K. S. Narendra, "Intelligent control using neural networks and multiple models," in *Proceedings of the 41st IEEE Conference on Decision and Control, 2002.*, vol. 2, Dec 2002, pp. 1357–1362 vol.2.

[37] S.-H. Yu and A. M. Annaswamy, "Neural control for nonlinear dynamic systems," in *Advances in Neural Information Processing Systems 8*, D. S. Touretzky, M. C. Mozer, and M. E. Hasselmo, Eds. MIT Press, 1996, pp. 1010–1016. [Online]. Available: http://papers.nips.cc/paper/1043-neural-control-for-nonlinear-dynamic-systems.pdf

[38] J. Yao, X. Wang, S. Hu, and W. Fu, "Adaline neural network-based adaptive inverse control for an electro-hydraulic servo system," *Journal of Vibration and Control*, vol. 17, no. 13, pp. 2007–2014, 2010. [Online]. Available: http://dx.doi.org/10.1177/1077546310395972

[39] K. Nouri, R. Dhaouadi, and N. B. Braiek, "Adaptive control of a nonlinear dc motor drive using recurrent neural networks," *Applied Soft Computing*, vol. 8, no. 1, pp. 371–382, 2008. [Online]. Available: http://dx.doi.org/10.1016/j.asoc.2007.03.002

[40] M. Aamir, "On replacing PID controller with ANN controller for DC motor position control," *CoRR*, vol. abs/1312.0148, 2013. [Online]. Available: http://arxiv.org/abs/1312.0148

[41] S. Kumarawadu and W. U. N. Fernando, "Discrete-time neuroadaptive control using dynamic state feedback with application to vehicle motion control for intelligent vehicle highway systems," *IET Control Theory and Applications*, vol. 4, no. 8, pp. 1465–1477, 2010. [Online]. Available: http://dx.doi.org/10.1049/iet-cta.2009.0144

[42] M. Brdys and G. Kulawski, "Dynamic neural controllers for induction motor," *IEEE Transactions on Neural Networks*, vol. 10, no. 2, pp. 340–355, 1999. [Online]. Available: http://dx.doi.org/10.1109/72.750564

[43] G. . Kim, I. . Ha, M. . Ko, and H. . Bae, "Control of induction motors for both high dynamic performance and high power efficiency," in *Proceedings IECON '91: 1991 International Conference on Industrial Electronics, Control and Instrumentation*, Oct 1991, pp. 787–792 vol.1.

[44] L. Meng, P. Wang, Z. Liu, R. Qiu, L. Wang, and C. X. Xu, "Safety assessment for electrical motor drive system based on som neural network," *Mathematical Problems in Engineering*, 2016.

[45] S.-Y. Shao, W.-J. Sun, R.-Q. Yan, P. Wang, and R. X. Gao, "A deep learning approach for fault diagnosis of induction motors in manufacturing," *Chinese Journal of Mechanical Engineering*, vol. 30, no. 6, pp. 1347–1356, Nov 2017. [Online]. Available: https://doi.org/10.1007/s10033-017-0189-y

[46] E. Ali, J. Weber, and M. Wahler, "A machine learning approach for tracking the torque losses in internal gear pump - ac motor units," *Intelligent Control*.

[47] R. Zhang, Z. Peng, L. Wu, B. Yao, and Y. Guan, "Fault diagnosis from raw sensor data using deep neural networks considering temporal coherence," *Sensors*, vol. 17, no. 3, p. 549, 2017. [Online]. Available: https://doi.org/10.3390/s17030549

[48] A. A. Silva, A. M. Bazzi, and S. Gupta, "Fault diagnosis in electric drives using machine learning approaches," in *2013 International Electric Machines Drives Conference*, May 2013, pp. 722–726.

[49] Y. L. Murphey, M. A. Masrur, and Z. Chen, "Fault diagnostics in electric drives using machine learning," in *Advances in Applied Artificial Intelligence*, M. Ali and R. Dapoigny, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 1169–1178.

[50] Y. L. Murphey, M. A. Masrur, Z. Chen, and B. Zhang, "Model-based fault diagnosis in electric drives using machine learning," *IEEE/ASME Transactions on Mechatronics*, vol. 11, no. 3, pp. 290–303, June 2006.

[51] D. George, H. Shen, and E. A. Huerta, "Glitch Classification and Clustering for LIGO with Deep Transfer Learning," in *NiPS Summer School 2017 Gubbio, Perugia, Italy, June 30-July 3, 2017*, 2017.

[52] K. A. Marko, "Neural network application to diagnostics and control of vehicle control systems," in *Advances in Neural Information Processing Systems 3*, R. P. Lippmann, J. E. Moody, and D. S. Touretzky, Eds. Morgan-Kaufmann, 1991, pp. 537–543. [Online]. Available: http://papers.nips.cc/paper/344-neural-network-application-to-diagnostics-and-control-of-vehicle-control-systems.pdf

[53] H. J. Kim and A. Y. Ng, "Stable adaptive control with online learning," in *Advances in Neural Information Processing Systems 17*, L. K. Saul, Y. Weiss, and L. Bottou, Eds. MIT Press, 2005, pp. 977–984. [Online]. Available: http://papers.nips.cc/paper/2623-stable-adaptive-control-with-online-learning.pdf