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INTELLIGENT CONTROLS AND MODELING FOR PARTICLE ACCELERATORS AND OTHER RESEARCH AND INDUSTRIAL INFRASTRUCTURES

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Abstract

We give some perspective on the present state of intelligent control for particle accelerators. This is based on our experience over the past 14 years in developing artificial-intelligence-based tools specifically to address modeling and control challenges found in particle accelerator systems.

INTRODUCTION

Despite the rush to incorporate artificial intelligence (AI) into every component of our lives, not all systems (or subsystems) require intelligent control or data analysis for reliable operation. As the old saying goes, "Just because you can [build it/use it] doesn't mean you should." Some systems, however, can greatly benefit from the responsible and well-architected incorporation of control techniques with intelligent characteristics.

Although other fields, such as computer vision and web search engines, were quick to adopt AI or AI-like tools, the field of accelerator physics has been more reluctant. However, things have advanced in several areas, such as computing and data collection, and these advances have truly enabled the research and subsequent application of AI techniques to particle accelerator. But, as with anything new, the APS News (June 2018, "AI Makes Inroads in Physics") notes there are still challenges [1].

Here we review several examples of complex systems that can benefit from intelligent control methodologies, i.e., cases that were otherwise under-responsive when simpler, less advanced approaches were applied. The case examples on which we focus deal with particle accelerators that are used in many disciplines including fundamental discovery science and engineering.

ACCELERATOR CHALLENGES INTERESTING FOR INTELLIGENT CONTROL AND MODELING SCHEMES

Upon examining the machines used for physics we note that since 1938, accelerator science has an estimated influence on almost one-third of physicists and physics studies, and on average contributed to physics Nobel Prize-winning research every 2.9 years [2]. Further, as one example of the prevalence of particle accelerators, we look to the United States. In support of its science mission, the U.S. Department of Energy (DOE) operates large scientific instruments that support the work of more than 50,000 scientists worldwide. Large particle accelerators are at the core of eleven of the seventeen National User Facilities that DOE operates. Particle accelerators also have roles in the industrial, medical, security, defense, environmental, and energy sectors. The performance goals and complexities of particle accelerators are ever increasing to meet the needs of the science and applications.

Several characteristics of the more complex existing and future particle accelerators are interesting for employing intelligent controls or modeling schemes. For instance, there are many parameters to monitor and control in various sub-systems, and accelerators have many interacting sub-systems. Applications can have on-demand, fast changes in the accelerator operational states. Accelerators can have many small, compounding errors. The accelerator physics of certain machines can be riddled with complex and/or non-linear dynamics having potential detrimental instabilities or other collective effects for effective machine operation. Often, the machine model does not resemble the as-built machine, so there are challenges in diagnosing and/or interpreting the operational behavior from day one of operation. Accelerator systems often exhibit time-varying and non-stationary behavior. Diagnostics for the beam, systems, and peripherals are also often limited because of cost, space, and the inability to physically characterize the overall system at all locations. In addition, even when diagnostics are in existence, they are often not put to full use in control schemes (e.g., images). A final concern is that systems or system peripherals are re-purposed in "new" machines, meaning that the equipment was not originally intended for use in such a configuration/specification.

WHAT DO ARTIFICIAL INTELLIGENCE (AI) AND RELATED TERMS MEAN?

The exact definitions of artificial intelligence and its related techniques are somewhat fluid in terms of interpretation in the community. Figure 1 attempts to help the reader classify the areas of artificial intelligence and related areas covered in this paper [3].

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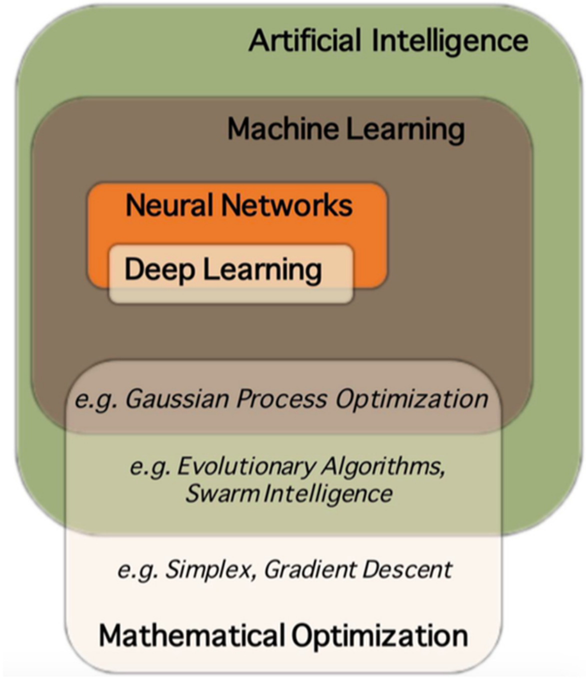

Figure 1: Classification space of artificial intelligence (AI) and related techniques [3].

Artificial intelligence is the concept of enabling machines to have intelligence similar to that of living beings. Where mathematical optimization involves the minimization or maximization of some objective function to select a target with regard to some criteria, machine learning allows some representation of the data to be learned and put to use in a specific task. Neural networks are a common method of machine learning employing many integrated processing units. There are many genres of neural networks and schemes for their training. Deep learning is concerned with hierarchical representations and is often equated with many-layered neural networks.

HOW TO USE AI CONCEPTS FOR ACCELERATORS

AI-based and related concepts can feed into controls engineering and takes inspiration from actual operators of the system. How? These concepts incorporate optimization (finding sweet spots), model learning, planning and prediction, learning control, diagnostic analysis, and system constraints into their models.

EXAMPLES OF RECENT AI-BASED CONTROLS ACTIVITIES

Our team has conducted design architectures and simulations [4] and proof-of-principle experiments in artificial-intelligence-based control of particle accelerators. Here we describe several examples.

On beamlines at the Australian Synchrotron, the Linac Coherent Light Source (LCLS), and the Fermi@Elettra at Sincrotrone Trieste [5-10], we were able to experimentally stabilize the electron beam energy and energy spread in the presence of klystron phase and amplitude jitter. We also demonstrated a novel controller that maintains maximum transmission through the machine.

The resonant frequency of a normal-conducting, radio-frequency (rf) electron gun is controlled thermally with a circulating water system adjusted as needed to the required temperature. At Fermilab, we were able to demonstrate better control of a water system with long, variable time delays due to large thermal time constants and variable rates of water transport. The existing PI controller for this system was unable to stabilize the temperature quickly and produced a large overshoot. For example, in a 1 °C change in the temperature set point of the gun, it takes approximately 25 minutes to settle and produces a maximum overshoot of > 0.5 °C. Using the method of an applied model predictive control (MPC) with a neural network model trained on measured data, the temperature was fixed in under six minutes and without overshoot [11-12].

In another normal-conducting device at Fermilab (a high-intensity, radio-frequency quadrupole (RFQ) to be used for the PIP-II upgrade program) we developed a resonance control system exploring several approaches, including a neural network control policy [13-15].

With the Thomas Jefferson National Accelerator Facility (JLAB) we have been collaborating on approaches for automatic steering tune-up on the now former free-electron laser (FEL) recovery linac. After taking data during tune-up and machine studies, a neural network (NN) model learned the beam position monitor responses to changes in dipole and quadrupole magnets. By interacting with the model, an NN control policy was then used to quickly jump to desired trajectories with specified position offsets [12,16-17].

We are also exploring ways to rapidly switch between operational set-points, such as two output wavelengths in a FEL user facility, or different beam energies in inspection systems. Using a neural network control policy trained over a broad range of operating conditions, one may be able to quickly and automatically execute these actions (for example, switching between different energies while maintaining a match to the undulator [18]).

Another area of exploration involves using a convolutional/fully-connected NN to predict downstream beam parameters for certain machine set-points; this is an important first step toward creating an NN controller that can directly use image diagnostics [19].

CONCLUSIONS

Our collaborations have made some of the first implementations on accelerators around the globe. Additional activities through new grants and contracts will permit additional progress for our community.

In the last ten months, three workshops have been held demonstrating the interest in artificial intelligence techniques as applied to particle accelerators as well as physics in general. The first, “Intelligent Controls for Particle Accelerators,” was held 30-31 January 2018 at Daresbury Laboratory [20]. The second, “ICFA Beam Dynamics Mini-Workshop: Machine Learning Applications for Particle Accelerators,” was held 27 February-2 March 2018 at SLAC

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[21]. The third, "Physics Next: Machine Learning," was held by the American Physical Society Physical Review publications group in New York on 8-10 October 2018 [22].

Outside of research and discussions on the technical aspects of artificial intelligence techniques, there are also important ethical discussions underway regarding these powerful tools. The Institute of Electrical and Electronics Engineers (IEEE) is actively engaged in investigating these topics. One significant IEEE activity, established in 2016, is the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems. It is an open, global, and inclusive (regionally, culturally, gender, etc.) community of experts and interested persons from technology and human science. Its mission is to ensure that every stakeholder involved in the design and development of autonomous and intelligent systems is educated, trained, and empowered to prioritize ethical considerations so that these technologies are advanced for the benefit of humanity. One outcome from this initiative is a standard [23]. In addition, the IEEE P7000 series of standardization projects is an ongoing process that seeks to gather more concrete guidelines through consensus in a meaningful time frame [24].

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