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ADAPTIVE MACHINE LEARNING AND FEEDBACK CONTROL FOR AUTOMATIC PARTICLE ACCELERATOR TUNING*

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Abstract

Free electron lasers (FEL) and plasma wakefield accelerators (PWA) are planning to create more and more complicated electron bunch configurations, including multi-color modes for FELs such as LCLS and LCLS-II and custom tailored bunch current profiles for PWAs such as FACET-II. These accelerators are also producing shorter and higher intensity bunches than before and require an ability to quickly switch between many different users with various phase space requirements, exotic setups require lengthy tuning. We present adaptive machine learning and model independent feedback techniques and their application in both the LCLS and European XFEL to control electron bunch longitudinal phase space (LPS) to create desired current profiles and energy spreads by tuning FEL components automatically, maximize the average pulse output energy of FELs by automatically tuning over 100 components simultaneously, and create non-invasive LPS diagnostics at PWAs.

AUTOMATIC ACCELERATOR TUNING

Precise control of bunch lengths, current profiles, and energy spreads of increasingly shorter electron beams at femtosecond resolution is extremely important for all advanced particle accelerators, including free electron lasers (FEL). FEL X-ray bursts with tunable wavelength are generated by tuning the energies of extremely short electron bunches (~fs). Two of the most advanced FELs are the Linac Coherent Light Source (LCLS) and the European XFEL (EuXFEL). The LCLS provides users with photon energies of 0.27 keV to 12 keV based on electron bunches with energies of 2.5 GeV to 17 GeV with electron bunch charges ranging from 20 pC to 300 pC and the bunch duration from 3 fs to 500 fs [1–3]. The EuXFEL, utilizes electron bunches with energies of up to 17.5 GeV, with charges ranging from 0.02 to 1 nC per bunch, and photon energies of 0.26 keV up to 25 keV [4]. Both the LCLS and the EuXFEL face challenges in quickly tuning between different beam types and achieving precise control for desired current and energy profiles and complex experiments such as two color mode and self seeding [5–8]

Extremum Seeking

The tuning algorithm that we utilized is based on a model-independent adaptive extremum seeking (ES) feedback approach developed for the stabilization of unknown, nonlinear, unstable dynamic systems. The main strengths of the method are that it works based on noisy measurements, can handle nonlinear, time-varying systems, and can tune many parameters simultaneously. Analytic proofs of convergence for a wide range of systems can be found in the literature [9–13].

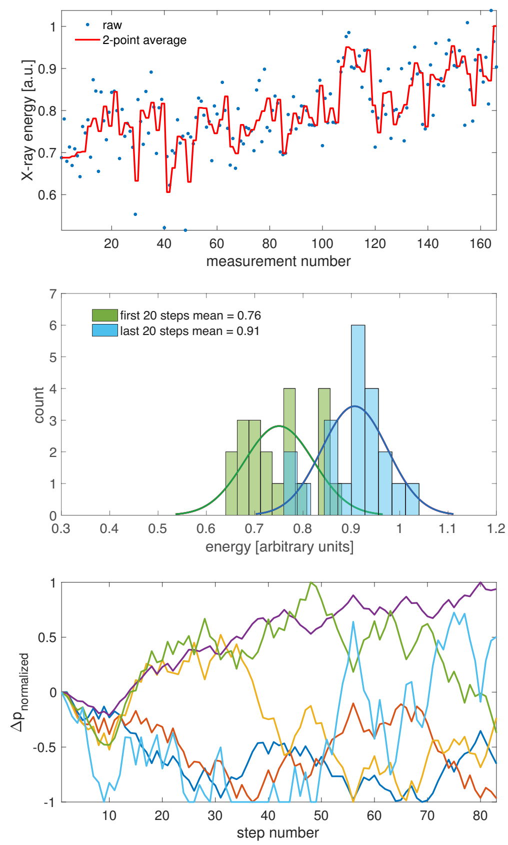

Figure 1: Maximization of nosiy pulse energy measurement at LCLS using only 2 point moving average.

For iterative accelerator tuning applications, we consider some analytically unknown cost function that we would like to minimize or maximize base only on noisy measurements, $C(\mathbf{p}, t)$. For this work, $C(\mathbf{p}, t)$ is the pulse energy of the light generated by an FEL and we would like to automatically maximize this cost function. This cost is a function of accelerator parameters $\mathbf{p} = (p_1, \ldots, p_m)$, such as magnet power supply settings which control magnetic field strengths or RF system phase and amplitude settings, which control the acceleration of the charged particle beams. Furthermore, all of these components, the beam itself, and the diagnostics drift with time due to external influences such as temperature variation, and therefore there is a time dependence. Also, we are usually only able to sample a noise-corrupted version of such a cost, of the form $\hat{C}(\mathbf{p}, t) = C(\mathbf{p}, t) + n(t)$. Although the interaction of charged particles with external sources of electromagnetic fields, including RF cavities, magnets, and other particles in the bunch, is analytically described via

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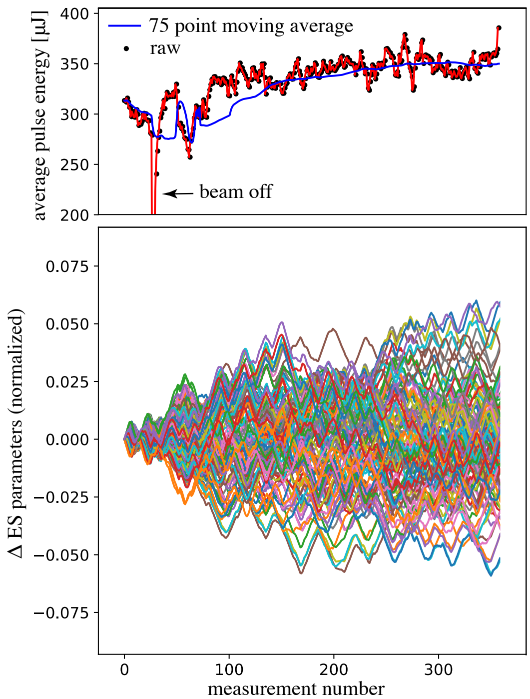

Figure 2: Tuning 105 parameters to maximize average bunch energy based on raw function measurements. The 75 point moving average is plotted to help visualize energy evolution.

Maxwell's equations and special relativity, when considering a realistic electron bunch and its travel down the length of a particle accelerator, there is no analytic formula relating all component settings to the light pulse energy.

Tuning of parameters **p** is based on the dynamics:

$$\frac{dp_i}{dt} = \sqrt{\alpha\omega_i}\cos\left(\omega_i t + k\hat{C}(\mathbf{p},t)\right), \qquad (1)$$

where all of the frequencies are distinct, $\omega_i = \omega r_i \neq \omega r_j = \omega_j$, a good way to choose the dithering frequencies ω_j is to evenly space them in the range $[\omega, 1.75\omega]$, for large ω, so that no two dithering frequencies are integer multiples of each other. α is related to the dithering amplitude of each parameter, upon reaching equilibrium, each parameter oscillates with an amplitude of $\sqrt{\frac{\alpha}{\omega_j}}$ about a steady state value, and k is a gain. Based on [9–13], one can prove that on average, for large ω_i, the dynamics of (1) are

$$\frac{dp_i}{dt} = -\frac{k\alpha}{2}\frac{\partial C(\mathbf{p},t)}{\partial p_i}, \qquad (2)$$

a gradient descent of the analytically unknown function C, despite only seeing its noisy measurement $\hat{C}$.

For digital iterative parameter updates, a finite difference approximation of the derivative in (1) is utilized:

$$p_i(n+1) = p_i(n) + \Delta_t\sqrt{\alpha\omega_i}\cos\left(\omega_i n\Delta_t + k\hat{C}(n)\right), \qquad (3)$$

where Δ_t is chosen such that $\Delta_t < \frac{2\pi}{5\max\omega_i} \ll 1$, so that the finite difference approximation of the derivative holds.

In practice, the iterative scheme is applied as follows: 1). Initial parameter settings, $\mathbf{p}(1)$, are chosen and applied to the accelerator. 2). Wait for accelerator components to settle to their new set points, after some waiting time, T_w, which may be 1 second for mechanical phase shifters and 0.1 seconds for digital RF set-points. 3). Once the accelerator parameters have settled to prescribed settings, record the cost function, $\hat{C}(1)$. 4). Calculate new parameter settings, $\mathbf{p}(2)$, based on $\mathbf{p}(1)$ and $C(1)$, as prescribed by (3), and continue iteratively.

The physical parameter update period, T_w, and the digital algorithm's numerical time step, Δ_t, are two completely independent quantities. In the digital algorithm, Δ_t is chosen to be arbitrarily small, based on dithering frequency choices, as described above. The update time, T_w, is the physical time between parameter updates and is chosen based on how fast accelerator parameters can be adjusted.

The ES scheme has been applied at FACET to create a non-invasive longitudinal phase space diagnostic, by adaptively tuning a model to match a non-destructive energy spread spectrum. Once this match was accomplished, the model's accurately predicted and tracked the longitudinal phase space (LPS) of the electron beam [13]. Further work in this direction is ongoing for even more accurate LPS predictions at FACET-II. We utilized the ES scheme for automatically maximizing the average pulse energy of both the LCLS and the EuXFEL FELs [14]. In Fig. 1 we see the results of automatic tuning 6 RF parameters at the LCLS where a simple 2-point average of the noisy pulse energy measurement was used as our $\hat{C}(\mathbf{p},t)$, running at ~1 Hz, so that the RF system had time to make prescribed adjustments. Figure 2 shows the results of applying the same technique at the EuXFEL with 105 parameters (84 air coils and 21 phase shifters) and a noisy cost function without averaging. This was during initial machine setup in which various parts are incrementally tuned to establish SASE.

Adaptive Machine Learning

Due to a sharp increase in availability of computational power, as well as the development of new algorithms, machine learning (ML) and in particular the use of neural networks (NN) has become very popular recently [15, 16]. Recently applications of ML to accelerators include parameter tuning [17], beam diagnostics [18], and LPS predictions [19]. Whereas a model-independent method, such as ES, can handle time-varying systems, it is a local approach and can possibly get stuck in local minima. Trained NNs can tune globally, but only for the data sets they were trained on, and therefore cannot handle time-varying systems. Therefore, we created an adaptive ML framework in which a trained NN takes a first global guess and then adaptive feedback is turned on and zooms in on and track time-varying optimal parameters. The approach was to train an NN based on a parameter scan, where for each parameter setting of the LCLS, we recorded a TCAV image of the LPS, to learn how to map phase spaces to parameters [20]. In Fig. 3 we demonstrate the ability of the adaptive machine learning approach. To achieve a desired phase space, a first guess for machine pa-

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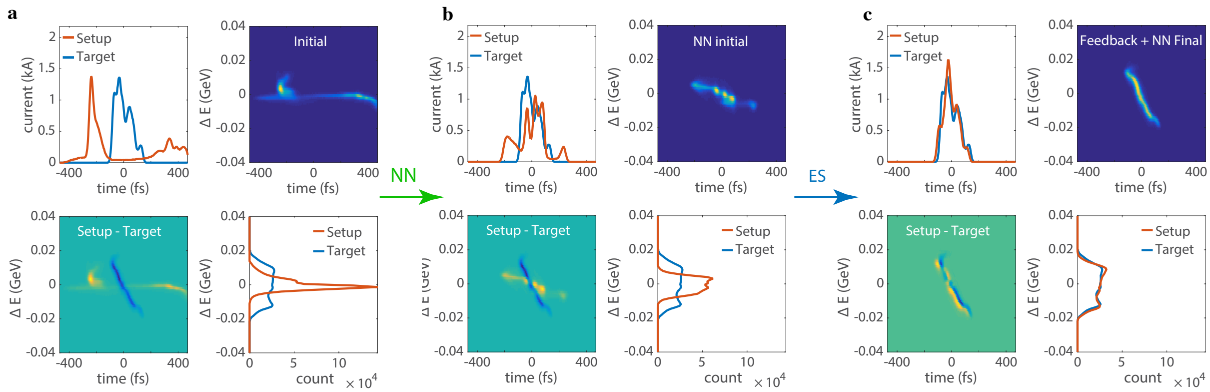

Figure 3: Automatically tuning accelerator parameters to achieve a desired longitudinal phase space in the LCLS.

rameters via a train NN takes place (**a**), ES is then applied ES based on real time TCAV measurements where the cost is the difference between the desired and current 2D phase space images (**b**), resulting in convergence (**c**).

CONCLUSION

We have demonstrated the ability of an adaptive feedback control method to automatically tune multiple accelerator components for maximization of average pulse energy at both the LCLS and the EuXFEL with very noisy signals. We have also demonstrated an adaptive ML approach for global tuning for time-varying systems. Future work will extend these techniques to larger parameter spaces.

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