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ADAPTIVE FEEDBACK FOR AUTOMATIC PHASE-SPACE TUNING OF ELECTRON BEAMS IN ADVANCED XFELS

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Abstract

Particle accelerators are extremely complex devices having thousands of coupled, nonlinear components which include magnets, laser sources, and radio frequency (RF) accelerating cavities. Many of these components are time-varying. One example is the RF systems which experience unpredictable temperature-based perturbations resulting in frequency and phase shifts. In order to provide users with their desired beam and thereby light properties, LCLS sometimes requires up to 6 hours of manual, experience-based hand tuning of parameters by operators and beam physicists, during a total of 12 hours of beam time provided for the user. Even standard operational changes can require hours to switch between user setups. The main goal of this work is to study model-independent feedback control approaches which can work together with physics-based controls to make overall machine performance more robust, enable faster tuning (seconds to minutes instead of hours), and optimize performance in real time in response to un-modeled time variation and disturbances.

INTRODUCTION

While existing and planned free electron lasers (FEL) have automatic digital control systems, they are not controlled precisely enough to quickly switch between different operating conditions. Existing controls maintain components at fixed set points, which are set based on desired beam and light properties, such as, for example, the current settings in a bunch compressor's magnets. Analytic studies and simulations initially provide these set points. However, models are not perfect and component characteristics drift in noisy and time-varying environments; setting a magnet power supply to a certain current today does not necessarily result in the same magnetic field as it would have 3 weeks ago. Also, the sensors are themselves noisy, limited in resolution, and introduce delays. Therefore, even when local controllers maintain desired set points exactly, performance drifts. The result is that operators continuously tweak parameters to maintain steady state operation and spend hours tuning when large changes are required, such as switching between experiments with significantly different current, beam profile (2 color, double bunch setups), or wavelength requirements. Similarly, traditional feed-forward RF beam loading compensation control systems are limited by model-based beam-RF interactions, which work extremely well for perfectly known RF and beam properties, but in practice are limited by effects which include un-modeled drifts and fluctuations and higher order modes excited by extremely short pulses. These limitations have created an interest in iterative (beam-based feedback), machine learning, and adaptive techniques.

The focus of this work is on minimizing the lengthy (1-10 hours) suboptimal manual tuning is required when beam parameters are changed between experiments, especially when settings of the low energy beam sections (<500 MeV) are changed. The sources of tuning difficulty include complex effects such as: space charge and coherent synchrotron radiation, which depend on many machine settings simultaneously, unobservable parameters, which are not well controlled, and time varying, drifting components. Such difficulties will only increase as existing and future light are exploring new and exotic schemes such as two-color operation (LCLS, LCLS-II) and next generation light sources seek to provide brighter, shorter wavelength (0.1nm at PAL, 0.05 nm at EuXFEL, and 0.01 nm at MaRIE), more coherent light [1]. To achieve their performance goals, new machines face unique challenges, such as requiring extremely low electron beam emittance and energy spread. LCLS-II requires <0.01% rms energy stability, which is >10x more than the existing LCLS linac [2]. EuXFEL requires < 0.001 %/deg rms RF amplitude and phase errors, respectively (current state of the art is 0.01) [3]. Existing and future accelerators will benefit from an ability to quickly tune between experiments and to compensate for extremely closely spaced electron bunches, such as might be required for MaRIE, requiring advanced controls and approaches such as droop correctors [4, 5].

The type of tuning problems that we are interested in have recently been approached with powerful machine learning methods [6, 7], which are showing very promising results. Our approach to this problem is complementary to other machine learning methods in that instead of learning over long periods of time, we attempt to respond quickly in real time, based on very limited measurements. One possible limitation of our approach is that being a real time, local feedback, it may become trapped in a local minimum. Future plans exist for combining the work discussed here with machine learning. We utilize a novel model-independent extremum seeking (ES) based feedback scheme, which operates based only on noisy measurements without dependence on accurate system models [8, 9] and is closely related to vibrational control [10]. The advantages of this approach are:

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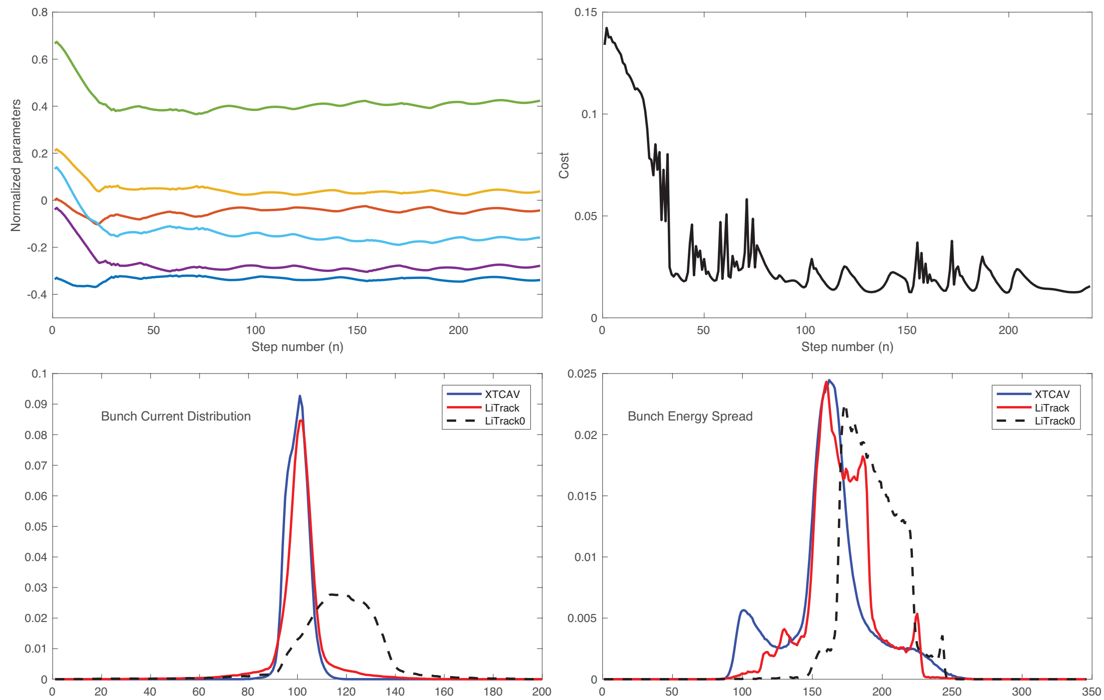

Figure 1: Parameter convergence and cost minimization for matching desired bunch length and energy spread profiles.

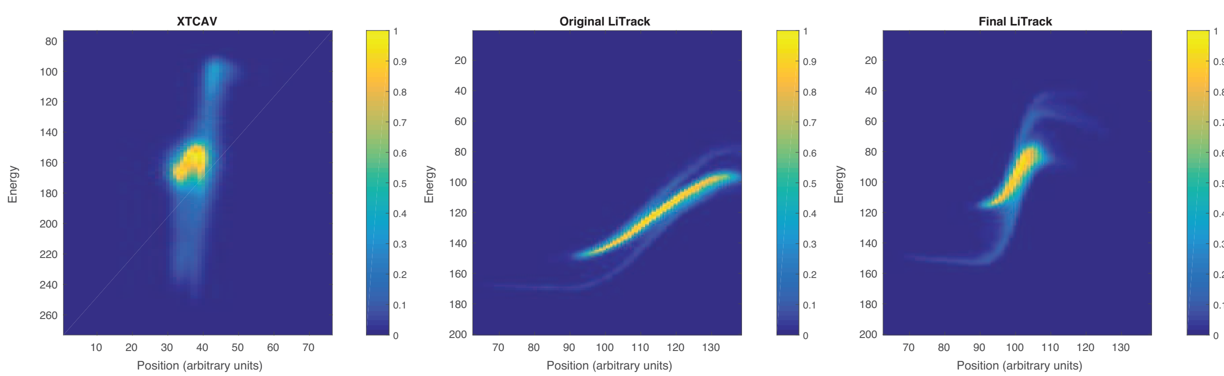

Figure 2: Measured XTCAV, original LiTrack and final, converged LiTrack energy vs position phases space of the electron bunch shown.

1. Multiple parameters tuned simultaneously.
2. The method is incredibly robust to noise, as has been demonstrated in hardware for tuning magnets [14].
3. Unlike genetic algorithms or simulation-based learning approaches, ES acts as a feedback directly on the actual system, adapting as things vary with time, and has analytically proven robustness, stability, and convergence rate estimates.
4. The parameter settings and update rates have analytically known, user-chosen bounds.

ITERATIVE EXTREMUM SEEKING

The ES method has been utilized in software and in hardware for automated particle accelerator tuning [11], electron bunch length prediction at FACET [13], in-hardware tuning of RF systems at LANSCE [12,15], and automated tuning of magnets in a time-varying lattice to continuously minimize betatron oscillations at SPEAR3 [14].

For the work described here, a measured XTCAV image was utilized and compared to the simulated energy and position spread of an electron bunch at the end of the LCLS as simulated by LiTrack. The electron bunch distribution is given by a function $\rho(\Delta E, \Delta z)$ where $\Delta E = E - E_0$ is energy offset from the mean or design energy of the bunch and $\Delta z = z - z_0$ is position offset from the center of the bunch. We worked with two distributions:

$$\text{XTCAV measured} : \rho_{\text{TCAV}}(\Delta E, \Delta z),$$
$$\text{LiTrack simulated} : \rho_{\text{LiTrack}}(\Delta E, \Delta z).$$

These distributions were then integrated along the E and z projections in order to calculate 1D energy and charge

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distributions:

$$\rho_{E,\text{TCAV}}(\Delta E), \quad \rho_{z,\text{TCAV}}(\Delta z),$$
$$\rho_{E,\text{LiTrack}}(\Delta E), \quad \rho_{z,\text{LiTrack}}(\Delta z).$$

Finally, the energy and charge spread distributions were compared to create cost values:

$$C_E = \int \left[\rho_{E,\text{TCAV}}(\Delta E) - \rho_{E,\text{LiTrack}}(\Delta E)\right]^2 d\Delta E, \quad (1)$$
$$C_z = \int \left[\rho_{z,\text{TCAV}}(\Delta z) - \rho_{z,\text{LiTrack}}(\Delta z)\right]^2 d\Delta z, \quad (2)$$

whose weighted sum was comined into a single final cost:

$$C = w_E C_E + w_z C_z. \quad (3)$$

Iterative extremum seeking was then performed via finite difference approximation of the ES dynamics:

$$\frac{\mathbf{p}(t+dt) - \mathbf{p}(t)}{dt} \approx \frac{d\mathbf{p}}{dt} = \sqrt{\alpha\omega}\cos(\omega t + kC(\mathbf{p}, t)), \quad (4)$$

by updating LiTrack model parameters, $\mathbf{p} = (p_1, \ldots, p_m)$, according to

$$p_j(n+1) = p_j(n) + \Delta\sqrt{\alpha\omega_j}\cos\left(\omega_j n\Delta + kC(n)\right), \quad (5)$$

where the previous step's cost is based on the previous simulation's parameter settings,

$$C(n) = C(\mathbf{p}(n)). \quad (6)$$

Machine tuning work has begun with general analytic studies as well as simulation-based algorithm development focused on the LCLS beam line, using SLAC's LiTrack software, a code which captures most aspects of the electron beam's phase space evolution and incorporates noise representative of operating conditions. The initial effort focused on developing ES-based auto tuning of the electron beam's bunch length and energy spread by varying LiTrack parameters in order to match LiTrack's output to an actual TCAV measurement taken from the accelerator by tuning bunch compressor energies and RF phases. The results are shown in Figures 1 and 2. Running at a repetition rate of 120 Hz, the simulated feedback would have converged within two seconds on the actual LCLS machine.

CONCLUSIONS

Preliminary results have demonstrated that ES is a powerful tool with the potential to automatically tune an FEL between various bunch properties such as energy spread and bunch length requirements by simultaneously tuning multiple coupled parameters, based only on a TCAV measurement at the end of the machine. Although the simulation results are promising, It remains to be seen what the limitations of the method are in the actual machine in terms of getting stuck in local minima and time of convergence. We plan on exploring the extent of parameter and phase space through which we can automatically move.

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