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SOLVING FOR COLLIDER BEAM PROFILES FROM LUMINOSITY JITTER WITH GHOST IMAGING

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Abstract

Large accelerator facilities must balance the need to achieve user performance requirements while also maximizing delivery time. At the same time, accelerators have advanced data-acquisition systems that acquire synchronous data at high-rate from a large variety of diagnostics. Here we discuss the application of ghost-imaging (GI) to measure beam parameters, switching the emphasis from beam control to data collection: rather than intentionally manipulating the accelerator, we instead passively monitor jitter gathered over thousands to millions of events to reconstruct the target of interest. Passive monitoring during routine operation builds large data sets that can even deliver higher resolution than brief periodic scans, and can provide experiments with event-by-event information. In this presentation we briefly present applications of GI to light-sources, and then discuss a potential new application for colliders: measuring the transverse beam shapes at a collider's interaction point to determine both the integrated luminosity and the spatial distribution of collision vertices.

INTRODUCTION

Modern accelerator systems record a wide range of diagnostics synchronously at high-rates. Traditionally, operators have exploited such data sets to search for unknown correlations from natural jitter during operation. More recently, advances in computational methods borrowed from machine learning point towards a new analysis paradigm in which operators *infer* measurements by fitting unknowns from synchronous diagnostics. One such approach is drawn from the concept of classical ghost imaging (GI), in which a series of known and varying illumination patterns probe a sample, and a 'bucket' detector measures a scalar value, e.g. total transmission, scattering, absorption, etc. (Note: we assume pixelated detectors are not available.) If the illumination patterns obey certain characteristics (independent pixels, sufficient degree of variation, etc.), it is possible to recover a so-called 'ghost' picture of the sample.

Broadly speaking, there are three advantages over the more traditional approach of raster-scanning a small probe over the sample [1]: First, if the bucket detector has Gaussian read-out noise, the multi-pixeled illumination patterns may give higher signal-to-noise ratio, known as the multiplex or Felgett's advantage [2]. Second, the reconstruction can be cast as an optimization task, and make use of prior knowledge to recover the solution in fewer measurements than would be needed for a raster scan, known as compressive GI [3, 4]. Third, it may be inconvenient or even impossible to create and scan a small probe. For example, scanning a probe may interfere with operations, or it may be possible to measure smaller features in the illumination patterns compared to the smallest achievable size of the scan probe.

For accelerators, the third advantage – leveraging jitter for passive measurements – has long proved useful. As far back as the 80s, Lohse and Emma used a forward model and beam jitter to learn BPM resolutions at the interaction point of the Stanford Linear Collider [5]. GI now has renewed relevance due to advances in the intervening decades in computational methods (e.g. compressive sensing [3]), optimization tools (e.g. ADMM [6]), and computational power (faster CPUs, GPUs), pointing towards efficient solution of complex problems from large data sets. Just at SLAC, recent GI applications include solving for spatial maps of cathode quantum efficiency using drive-laser jitter [7], and increasing temporal [8] and frequency [1, 9] resolution for x-ray free-electron lasers using natural jitter in self-amplified spontaneous emission free-electron lasers.

In this paper, we consider the challenge of measuring the beam profiles at a collider's interaction points (IPs) and speculate that GI can help. The goal is two-fold: First, by resolving the beam profile, we can potentially assist operation to create more uniform, tightly-focused beams at the IPs, as well as provide consistent beam profiles across the various IPs. Second, if we can recover shot-by-shot measurements and beam profiles we can improve modeling of the interaction distribution for each event to improve analysis for experiments. Both goals can be achieved with passive measurements, without interrupting operations.

We can frame the collider IP problem as a form of ghost imaging: rather than a varying illumination pattern, we have a varying offset between two unknown beams, and the bucket measurement is the total luminosity. The current approach to measuring transverse beam profiles is to scan the offset between the colliding beams and fit the transverse beam dimensions to the drop in luminosity [10]. The GI approach switches the emphasis from beam control to data collection: rather than intentionally controlling the offset, we instead passively monitor random beam jitter, and use statistics gathered over millions of collisions to reconstruct the profile.

METHOD

Recovering beam parameters from orbit and luminosity measurements is an example of an inverse problem: The forward task of calculating luminosity from beam parameters is relatively simple, but the inverse task of predicting parameters given the luminosity and offset measurements is challenging. In this note we consider a toy forward model

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to calculate luminosity

$$\mathscr{L}_{\text{pred}}(I_1, I_2, \delta^{(k)}) = \int dv\, I_1(v) I_2(v - \delta^{(k)}) , \quad (1)$$

where v is the vector of transverse positions $[x, y]$, $I_{1,2}(v)$ are the transverse beam densities of the two colliding beams, and $\delta^{(k)}$ is the vector of horizontal and vertical offsets, $[\delta_x^{(k)}, \delta_y^{(k)}]$, between the two beams for the k^{th} collision. (Note that we ignore longitudinal variation.) Our goal is to invert the relationship to infer the 'most-likely' beam densities given many measurements of offsets and luminosities. With a dataset consisting of n measurements $\delta_x, \delta_y, \mathscr{L}_{\text{pred}} \in \mathbb{R}^n$, the solution to the inverse problem, $\hat{I}$, is given by the parameters that minimize the difference between the predicted and measured luminosities, i.e.

$$\hat{I}_1, \hat{I}_2 = \text{argmin}_{I_1, I_2} \sum_k \left| \mathscr{L}_{\text{pred}}(I_1, I_2, \delta^{(k)}) - \mathscr{L}_{\text{meas}}^{(k)} \right|, \quad (2)$$

where $\mathscr{L}_{\text{meas}}^{(k)}$ is the measured luminosity, and $\mathscr{L}_{\text{pred}}(I_1, I_2, \delta^{(k)})$ is the predicted luminosity from the forward model, Eq. (1), for the k^{th} collision.

If we represent the beam profiles, I, as a pixelated image, Eq. (2) is a high-dimensional optimization problem with each pixel a separate parameter. The challenge is compounded by the presence of noise and errors on the measurements, such that even with perfect knowledge of the forward model, we still expect $\mathscr{L}_{\text{pred}}$ and $\mathscr{L}_{\text{meas}}$ to differ. We can improve the reconstruction through the addition of 'regularization' terms to Eq. (2), imposing our prior beliefs about the solution to constrain the optimization, known as compressive GI [4]. Alternatively, we can impose priors through parameterization of I. For example, for smooth Gaussian beams, if we assume the beam sizes are known, we can use the parameterization

$$I(v) = \exp\left\{-v^T R(\varphi) E(\varepsilon) R(-\varphi) v\right\} , \quad (3)$$

in which case we only need to learn four parameters $(\varepsilon_1, \varphi_1, \varepsilon_2, \varphi_2)$ to minimize Eq. (2). Here $R(\varphi)$ is a rotation matrix and the diagonal matrix $E(\varepsilon)$ imposes the eccentricity with on-axis elements $\sqrt{1-\varepsilon^2}$ and $1/\sqrt{1-\varepsilon^2}$. If we anticipate more complicated beams we can turn to higher-dimensional representations, e.g. learning Hermite-Gaussian representations with the degree constraining the complexity.

EXAMPLE WITH GAUSSIAN BEAMS

To investigate the feasibility, we take the case of small jitter in a Gaussian beam using Eq. (3), which makes the reconstruction challenging due to the small variation in luminosity. For this simple example, we can integrate Eq. (1) to find an analytical expression for the forward model

$$\begin{aligned}
\mathscr{L}_{\text{pred}} &= \frac{\pi e^{A/B}}{\sqrt{B}} \\
A &= (\delta_x^2 + \delta_y^2)\left[\xi_1 e_2^2 + e_1^2 \xi_2 - 2(\xi_1 + \xi_2)\right] + \\
&\quad (\delta_x^2 - \delta_y^2) e_1^2 \xi_2 \cos[2\varphi_1] + (\delta_x^2 - \delta_y^2)\xi_1 e_2^2 \cos[2\varphi_2] - \\
&\quad 2\delta_x \delta_y \left(e_1^2 \xi_2 \sin[2\varphi_1] + \xi_1 e_2^2 \sin[2\varphi_2]\right) \\
B &= [4 - 2(e_1^2 + e_2^2) + 4\xi_1\xi_2 + \\
&\quad e_1^2 e_2^2 \left(1 - \cos[2(\varphi_1 - \varphi_2)]\right)] ,
\end{aligned} \quad (4)$$

with shorthand $\xi_i = \sqrt{1 - e_i^2}$. Note that due to symmetries of both the Gaussian beams and forward models, there is not a unique solution, e.g. swapping the parameters of the two beams (i.e. $1 \leftrightarrow 2$) has no effect on Eq. (4).

Our goal is to resolve the angle and degree of eccentricity of both beams. Figure 1 shows example beams with eccentricity of $\varepsilon_1 = 0.5$ at an angle of $\varphi_1 = 1.0$ from the vertical for beam 1, and $\varepsilon_2 = 0.7$ at an angle of $\varphi_2 = 0$ for beam 2. We then simulate 100k collisions with different parameters. Figure 2 shows examples with zero jitter and noise (top plots) and moderate jitter and noise (bottom plots). Note that even the 'moderate' level of luminosity jitter is far higher than the 0.1% level observed in asynchronous sub-Hz measurements at LHC, which average across 10s of millions of collisions. However 1% may be a realistic jitter level if it is possible to measure individual collisions.

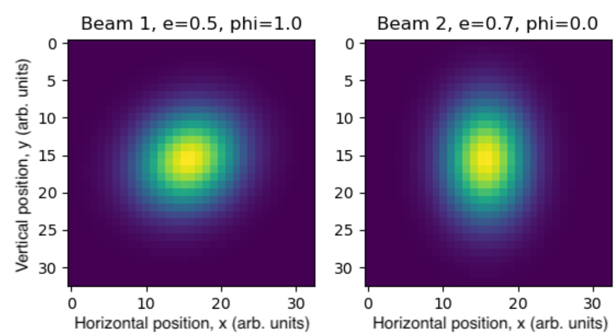

Figure 1: Simulated Gaussian beams for Fig. 2.

We observe mixed results. Figure 2 shows the negative log residual for different parameter choices, and as expected the maximal value is the true solution. However, several caveats point to difficulties for implementation. First, a scan with zero luminosity jitter shows potential symmetries that may lead to non-unique solutions. With the jitter at a still-optimistic 1%, the eccentricity solutions are only constrained to an arc (bottom left plot). On the other hand, we have only presented a simple concept here, and more sophisticated treatment may find a path forward. For example, integrating standard luminosity scans (i.e. scans with far higher luminosity jitter; in fact, this type of scans is already done routinely during fills at the LHC [10]) may improve constraints, as would simultaneously fitting data at multiple interaction points and modeling the evolution of Twiss parameters. Here we summarize steps towards implementation.

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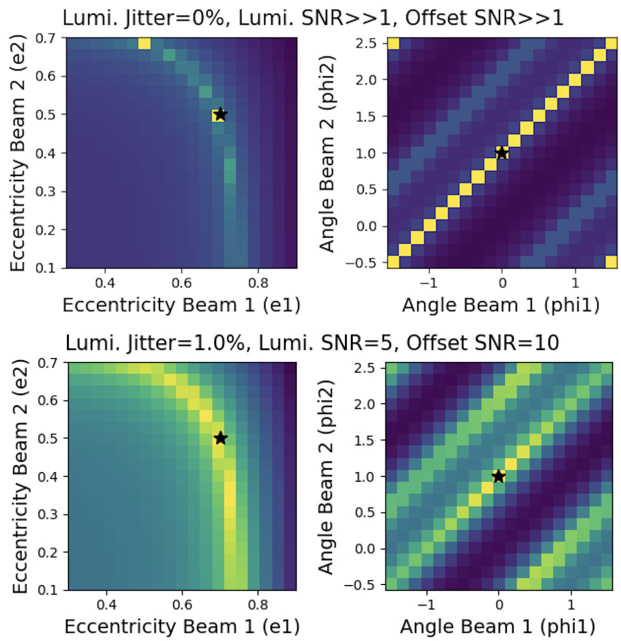

Figure 2: Negative log of residuals for parameter scan. On the left, scan of eccentricity for both beams, and on the right, scan of angle. All plots assume the correct ground truth value for non-scanned variables (angle at left, eccentricity at right). Black stars show ground truth values. SNR is defined as ratio of rms noise to rms variation. Top row shows an example without jitter or noise to illustrate symmetries, and lower plot shows the same scan with jitter and measurement noise included.

Data set size and variation Ideally we would have synchronous measurements of luminosity and orbit for each collision. Averaging over many pulses is possible, but degrades the data in the following ways:

- Longer averaging produces fewer data points.
- Longer averaging decreases the variability in the data, so more data is needed to solve Eq. (2). Intuitively, the less variability, the less information contained in each measurement. In standard linear ghost imaging this can be quantified by the Gramian of the data matrix.
- If we average over all the stored bunches we only reconstruct the average transverse profile of all bunches. We lose the knowledge of individual bunch variation, and also further reduce the amount of variability.

Averaging degrades data quality, both reducing the number of points and the degree of variation. On the other hand, we note that 10M collisions corresponds to only 15 minutes of LHC operation if development of a collision-by-collision monitor is possible. Even 1B collisions might be possible if combining data across different buckets. While we want variability in the orbit, we assume we have no change in the target beam shape (I) over the course of the measurement. In the end, the time-scale over which I changes sets the upper limit on the amount of data collected.

Non-unique solutions Because of the toy model's symmetry, the model described cannot distinguish between the two beams, and other symmetries may also pose challenges. Combining data from multiple IPs may break the symmetries, or the solver may require active control of the beam.

Orbit errors The accuracy of the orbit measurements will determine the resolution of the final reconstruction. In this proceeding we are using a highly simplistic model, but a more accurate model (e.g. fitting the orbit throughout the ring) may also break symmetries causing ambiguities in the current implementation.

Transverse-Longitudinal correlations Without additional diagnostics, or perhaps active beam control, we have no ability to reconstruct the beam's longitudinal profile.

CONCLUSION

We conclude that the GI approach to measuring beam profiles from luminosity is intriguing, but requires more study to assess feasibility. Additional information, for example by combining measurements from multiple interaction points, may be needed to distinguish ambiguities. Intentionally adding small deviations to the orbit – at a level that does not interfere with operations – or combining continuous jitter measurements with periodic luminosity scans, may also help. In the latter case, while no longer fully passive, still has the advantage of predicting luminosity distribution collision-by-collision. Finally, even if the concept presented here proves infeasible, we hope this proceeding can spur additional research into application of GI for colliders.

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