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# NON-DESTRUCTIVE DEFINITION OF EMITTANCE USING THE COMPTON BACK-SCATTERING AND AI MACHINE LEARNING

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*Abstract*

The goal of this work is to present the concept and the model for the reconstruction of the beam emittance from the spectrum of the Compton scattered photons using a machine learning procedure. The Compton process is the back-scattering of a laser pulse on the relativistic electron beam and is at the base of X-ray sources, as for instance, the project STAR. In the scattering process, the scattered photons get energy boost. The energy boosted photons carry also information about the transverse momentum of the initial electron bunch. In this work we present theory, model implementation and simulations on how the beam emittance can be estimated from the radiation spectrum.

## INTRODUCTION

The measurement of beam emittance, which characterizes the size and shape of a charged particle beam, is essential for the performance optimization of particle accelerators and other high-energy physics experiments. One of the most common methods for measuring beam emittance is through the use of destructive techniques, such as wire scanners or beam profile monitors. However, these methods are limited in their ability to provide precise and accurate measurements, and can also be time-consuming and costly.

An alternative method for non-destructive emittance measurements is through the use of Compton back scattering (CBS), which involves the back-scattering of a laser pulse on a relativistic electron beam [1–6]. In this process, the scattered photons gain energy and carry information about the transverse momentum of the initial electron bunch. The spectrum of the scattered photons can be used to reconstruct the beam emittance, providing a non-destructive and accurate measurement technique.

In this article, we present the concept and model for the reconstruction of beam emittance using Compton back-scattering and Artificial Intelligence (AI) machine learning. Our work focuses on the implementation of the theory behind the Compton process and the use of machine learning algorithms to analyze the scattered photon spectrum and reconstruct the beam emittance and spot size in the Compton interaction point (IP).

The presented method can be applied to a wide range of accelerator and X-ray source projects, such as the project STAR [7], and has the potential to revolutionize the field of beam diagnostics and characterization. With its non-destructive nature and high precision, the Compton scattering technique combined with machine learning analysis provides a powerful tool for optimizing the performance of particle accelerators and high-energy physics experiments. For the working point we take the high energy branch of STAR at 140 MeV. The list of parameters is presented in Table 1.

Table 1: STAR Parameters

| **Electron beam parameters** | |
|---|---|
| Energy (MeV) | 140 |
| Bunch charge (pC) | 500 |
| Energy spread (rms, %) | 0.24 |
| $\epsilon_{n,x,y}$ (mm mrad) | 1.32 |
| $\sigma e, x, y$ ($\mu m$) | 18 |
| Bunch length (rms, mm) | 0.66 |
| **Laser pulse parameters** | |
| Interaction angle (deg) | 5 |
| Pulse Energy (J) | 0.5 |
| Wave length (nm) | 1030 |
| $\sigma l, x, y$ ($\mu m$) | 10 |
| Pulse length (rms, ps) | 1 |

## THEORETICAL APPROACH

In the field of Compton backscattering (CBS) or inverse Compton scattering (ICS), the spectrum of scattered photons depends on various parameters of the initial electron bunch and laser pulse. The spectral bandwidth can be approximated by the scaling laws shown in Equation 1,

$$\frac{\delta E_{ph}}{E_{ph}} = \sqrt{\left(\frac{\sigma_\theta}{E_\theta} + \frac{\sigma_\varepsilon}{E_\varepsilon}\right)^2 + \left(\frac{\sigma_L}{E_L}\right)^2 + \left(\frac{\sigma_\gamma}{E_\gamma}\right)^2} \qquad (1)$$

where each term represents a corresponding contribution by kinematics of scattering $\left(\frac{\sigma_\theta}{E_\theta}\right)$, emittance $\left(\frac{\sigma_\varepsilon}{E_\varepsilon}\right)$, laser bandwidth $\left(\frac{\sigma_L}{E_L}\right)$ and energy spread of electrons $\left(\frac{\sigma_\gamma}{E_\gamma}\right)$. A more detailed discussion of this formula can be found in the works [8, 9].

The dependence of the spectrum on the spot size of the electron bunch at the interaction point (IP) is directly presented by the luminosity into the acceptance angle $\Psi = \gamma\theta_{max}$ (collimated) [10]:

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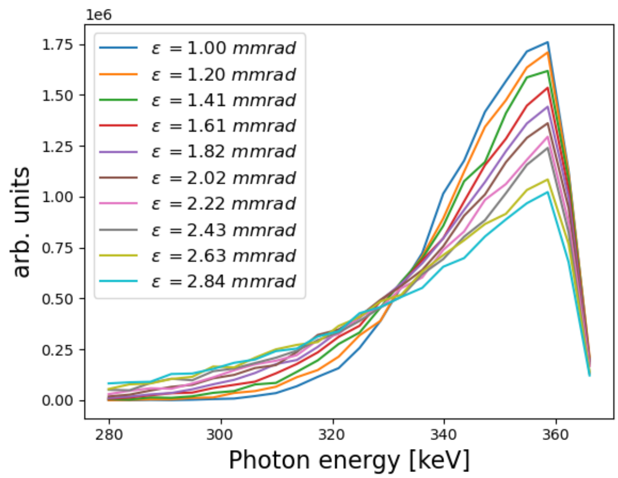


Figure 1: Effect of emittance on the spectrum of scattered photons. $\sigma_{x,y} = 15\ \mu m$

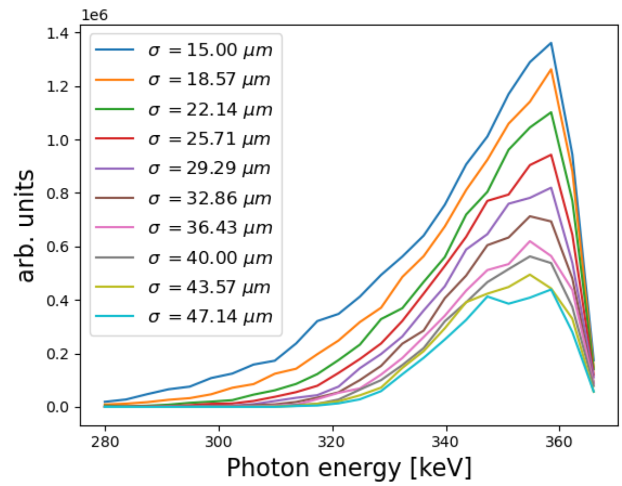


Figure 2: Effect of sigma on the spectrum of scattered photons. $\varepsilon_{x,y} = 2.02\ mmrad$

$$N^{\Psi} = \frac{f N_e N_L \int^{\Psi} d\Psi' \frac{d\sigma}{d\Psi'}}{2\pi \sqrt{\sigma_{y,e}^2 + \sigma_{y,L}^2}\sqrt{\sigma_{x,e}^2 + \sigma_{x,L}^2 + (\sigma_{z,e}^2 + \sigma_{z,L}^2)\tan\frac{\alpha}{2}}} \tag{2}$$

where $\sigma$ is the Compton cross section [11], $N_e$, $N_L$ are the number of interacting electrons and laser photons, $\sigma_x$ ($\sigma_{e,L}$) and $\sigma_y$ ($\sigma_{e,L}$) are the rms electron (laser) transverse dimensions at waist, $\sigma_z(\sigma_{e,L})$ is the electron (laser) beam length and $\theta_{max}$ is the maximum acceptance angle.

## SIMULATION AND DATA

In general, the dependence of the spectrum on the spot size (sigma) is more complicated due to the correlation between emittance and sigma, which becomes even more complex when the source is not a point-like. Analyzing all of these dependencies analytically can be extremely challenging. However, Monte Carlo simulations can be used to demonstrate these dependencies. Figure (1) presents the spectra (by default in this article we use collimation aperture $\theta = 1\ mrad$) for a fixed value of $\sigma_{e,x,y} = 15\ \mu m$ and varying emittance, instead, on fig 2, the value of emittance is fixed $\varepsilon_{x,y} = 2.02\ mmrad$.

From these two plots we can see that the effect of emittance is mainly to change the slope of the spectrum, while the effect of the spot size can be seen on the intensity. Fig. 3 presents a sample of 10 random spectra from 2500 used to educate the AI machine learning model. This set of simulations was done using code CAIN developed by Yokoya [12]. Parameters of the electron beam and the laser pulse are presented in table 1. To create the set of 2500 spectra, the emittance and the spot size were both varied; the emittance covered a range $\varepsilon_{x,y} = 1 - 3\ mmrad$ with 50 equal 50 steps; for each value of emittance, 50 simulations with varying beam spot size at IP in the range $\sigma_{e,x,y} = 15 - 50\ \mu m$ were performed. In parallel a similar set of simulations was done to create test data representing the output from experimental

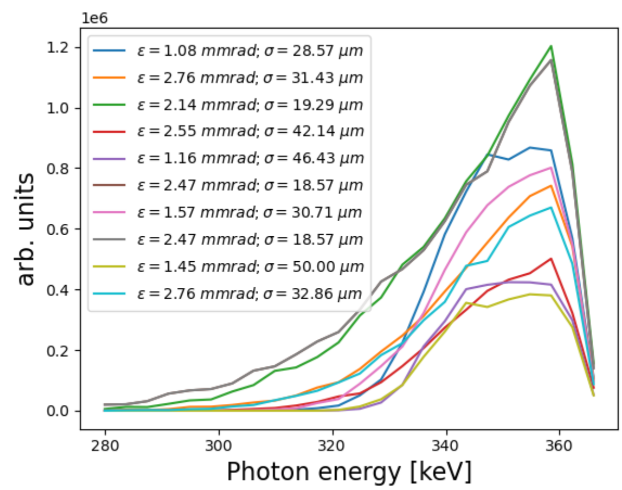


Figure 3: Sampling spectrums for random pair of spot sizes and emittances.

installation. The main difference in creation the set of the test data was that emittance and spot size was linearly spaced in 17 points each instead of 50. Using 17 as prime number give us set of values for emittance and spot size what will be not repeated in the education set.

On this figure 3 we can already notice that each spectrum has its own unique ”finger print” in the shape of slop and intensity.

Based on this we will build our model. The main idea of our model is to measure the emittance ($\varepsilon_{x,y}$) and spot size ($\sigma_{e,x,y}$) using the dependence described above by combining it with the AI based on machine learning.

Modern models of machine learning can work with different type of data. But since we are interested in low errors and getting high efficiency in definition of emittance and spot size, we need to prepare the set of spectra from simulations. Each spectrum (originally an histogram) was saved as one-dimensional vector with fixed minimal ($E_{ph} = 280\ keV$)

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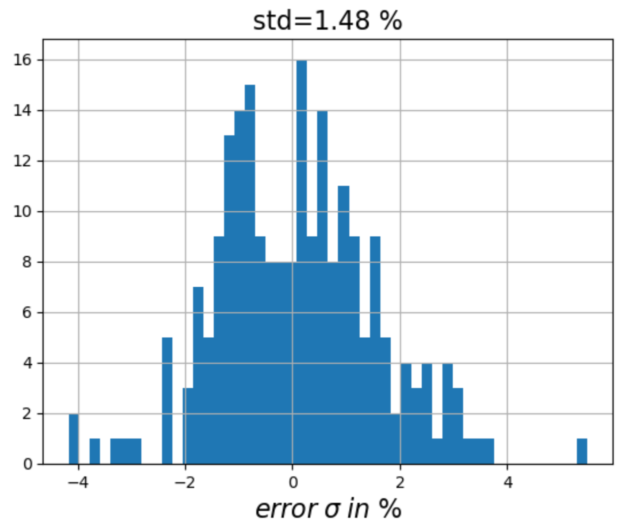


Figure 4: Distribution of errors in spot size predicting in the testing data

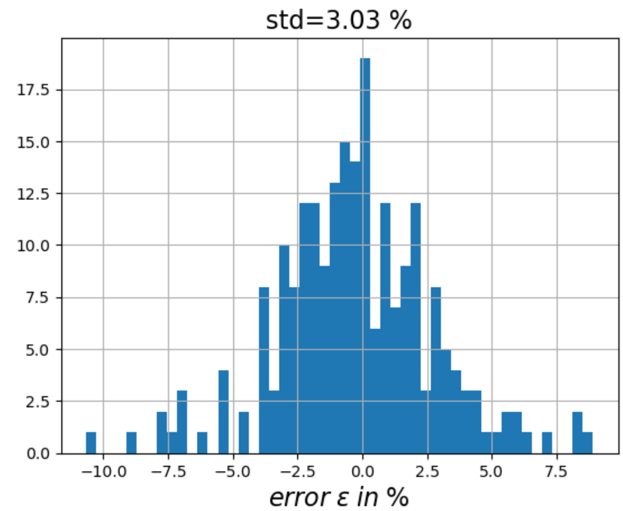


Figure 5: Distribution of errors in emittace predicting in the testing data

and maximal($E_{ph}$ = 280 $keV$) values of photon energy and fixed number of binnings ($N_{bin}$ = 20). Here it is important to notice that we do not need to normalise our spectra since we are interested in the number of photons per bin, and this will save information on how our spectrum depend from spot size. In addition, we add to each vector, as a label, values of emittance and spot size used as initial parameters for the simulation.

Thus, our original physic problem is reduced to a standard regression problem in Machine Learning.

Sklearn [13] model random forest regressor was chosen as Machine learning system, as one of the simplest and most suitable for working with our data.

For the educational stage of the process (in Sklearn, the "model.fit" routine), we use our prepared list of spectrum vectors as the training input samples and values of the emittance and spot size as the target values.

### *Errors*

In our case, the most important error is the error in definition of emittance and spot size. In the figures 5 and 4 we present the distribution of errors in the definition of emittance and spot size, respectively by machine learning compared with initial values used in the simulations for testing data set. As we can see, the rms error for beam spot size at IP is 1.5% and just 3% for definition of emittance value. The proposed method can be one of the precise diagnostic tools for the particle accelerators.

## CONCLUSION

In conclusion, this article presented a non-destructive method for measuring beam emittance using Compton backscattering (CBS) and AI machine learning. The concepts behind the CBS technique were explained, and the theory was implemented to reconstruct the beam emittance from the

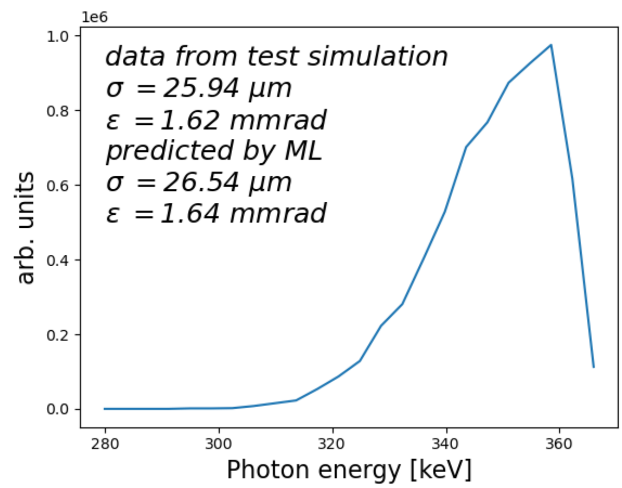


Figure 6: Example of prediction emittace and sigma for spectrum from tested data

spectrum of scattered photons. The authors demonstrated the potential of this method in optimizing the performance of particle accelerators and high-energy physics experiments, making it a valuable tool for the field of beam diagnostics and characterization.

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