A PEAK FINDING ALGORITHM FOR FEL SPECTRA CHARACTERIZATION

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Abstract

FELs are powerful investigation tools on the forefront of scientific discovery and with the addition of seeding capabilities their spectral brightness has improved drastically. It is therefore important to have reliable methods to judge the spectral quality. Emitted photons provide powerful information for assessing the performance of an FEL and troubleshooting issues that may arise in its operation. The spectrum is one of the most important characteristics of an FEL and a good estimate of the residual modes is crucial for experiments. Moreover, by analyzing the spectrum one can infer electron bunch properties.

INTRODUCTION

In this paper we present a new peak finding algorithm aimed to be integrated in FERMI’s pyDart [1] analysis software and which is now being extended to include new features. The pyDart tool takes in data from real time acquisition of different diagnostics of FERMI and, among other capabilities, plots correlations between values of an actuator and data from the detectors.

The analysis by the peak finding algorithm is done solely on spectral data. The desire is to produce a few figures of merit (fom) which closely relate on to a specific property of the spectra and in a scan follow its evolution w.r.t. an actuator value.

FEL radiation is sought by users for its coherence properties, while an FEL operating in SASE mode has many spikes giving an effective bandwidth close to 1%, it is expected from a seeded FEL such as FERMI to produce almost transform limited pulses [2]. All this means that a spectrum with a single, narrow peak is desired most of the time. Small modulations in the beam would produce, going into the radiator, sidebands to the main peak which means experiments would also get radiation at other wavelengths.

Although the program can offer a wide range of data about spectra we selected only a few fom that offer important information about the spectrum and implicitly on the effectiveness of the FEL process.

Am Area of the main peak scaled to the total area. This fom shows how much of the total power is carried in the main peak

mpd Mean peak distance is useful in estimating the possible source of the sidebands

1. Fitting Procedure

A critical component of the program regards the way in which the goodness of fit is estimated. The background evaluation is used here to weigh the different parts of the

ALGORITHM WORKFLOW

Through a sequence of steps the program finds and fits a number of peaks to a spectrum as shown in Fig.1. The top plot shows in red dots the detected peaks of the raw signal. The program evaluates the background of every spectrum and produces a set of criteria like height, prominence and minimum peak distance that a peak must satisfy for it to be detected. We use a customized version of the peak finding function in python scipy.optimize package [3] for this initial estimate. After detection each peak gets assigned corresponding valleys (blue dots) i.e. the limit where each peak effectively starts and ends. Once these regions of interest are obtained, a series of gaussian functions are fitted to each region, this intermediate step is presented in middle plot. After a fit is made we evaluate a goodness of fit function $gof$ and compare it to a preset value. In case the $gof$ is below this value a new fit function is proposed and a new fit is made.

Figure 1: The stages of the workflow: Identifying the peaks and valleys (top) fitting the gaussians (mid); computing the residual (bottom). Spectrum supplied by FERMI where microbunching is artificially induced with laser heater beating [4].

The algorithm treats each spectrum acquired during a scan individually and evaluates for each one the background region so noise in the detectors does not influence the quality of the peak detection. Furthermore there is an option to select the region considered to be background for each spectrum.
region to be fitted. For example, the weight function is 0 for features that are at or below the noise level and it asymptotically approaches unity for large features. This method for weighing ensures the tip of the peak, where there is less chance noise is an influence, counts most in the fitting procedure.

As seen in Fig.1, the largest peak has a shoulder towards higher wavelengths; this characteristic is quite common and obscures peaks from being detected. Such a feature means that some frequency component is overestimated or the total energy in a frequency component can be incorrectly estimated.

If in a region a simple gaussian fit function does not yield a good $gof$ we allow a multi gaussian fit function. To estimate the number of gaussians needed for the fit we analyze the residual between the current fit and the signal. If a certain fit quality is reached or if the maximum number of iterations has been performed we enter the final step where we discard those gaussians which do not produce a significant impact to the goodness of fit Fig.1 (bottom plot).

**BENCHMARKING FIGURES OF MERIT**

In this section we test the usefulness of a few figures of merit using data from un-optimized FERMI FEL II operating in HGHG fresh bunch mode.

**$Am$**

We benchmark our $Am fom$ against the intensity on a photodiode while scanning the delay between the first and second stage of the HGHG in Fig.2. Analyzing the plots we observe a profile resembling an electron beam bunch length measurement. It can be seen that the $Am$ parameter is not as sensitive to "bad" parts of the electron beam, as the intensity therefore it must be used in connection with a $a$ parameter that gives an absolute value for the pulse energy. Further observing the plots we can state that the $Am$ is not a measure of intensity but rather of the "cleanliness" of the spectrum and is therefore a good tool in detecting when the FEL process is disturbed.

**$Mpd$**

We test our mean peak distance $fom$ by trying to detect the modulation induced by the Laser heater beating in the electron beam. In seeded FEL, separation between sidebands is mostly determined by electron beam modulations that comes from microbunching instability or external modulation. Study of sidebands can help in determining electron beam properties. In Fig.3 we plot a spectrum in the case of a laser heater induced microbunching [4] in the electron beam. We plot the fitted signal and based on the position of the peaks we reconstruct the periodicity of the modulation present in bunch. Even though we restricted the number of peaks to be detected and therefore miss some intermediate peaks, the algorithm correctly identifies the separation because it calculates the common denominator between peak distances, allowing for a few pixels error.

The $mpd$ parameter is helpful in detecting microbunch instabilities generated by other sources such as coherent synchrotron radiation in the bunch compressors or errors in the cathode. By estimating the modulation one can make a more educated guess on the nature of the unwanted microbunching process.
FEATURES IN THE ANALYSIS

Due to the fact that the algorithm uses fitting methods it can find peaks that are hidden in a first estimation. To showcase one such example we observe Fig. 4. In this particular spectrum the main peak is flanked by two side peaks that all merge together. In trying to determine, for example, the peak spacing we would make a wrong estimate were it not for the peak detection algorithm.

Being designed to be used in connection with PyDart and the real time acquisition system at FERMI it has an operating mode that allows for fast identification of peaks with fitting just one gaussian to the main peak. This mode is sufficient for generating a FWHM number and a the Am fom. The execution time per spectrum with this mode is less than 50 ms. Another feature is the possibility to integrate the program with other software as the user has control in the format of the output by selecting maximum number of detected peaks and length of data.

Future Word

In our analysis we have found that each detector has a constant background component that appears in every spectrum. A future improvement should be to estimate this constant background for different intensities and produce a lookup table with data that should be subtracted from the spectra. In an effort to more accurately detect the microbunching we will modify the procedure to account for beams that do not have uniform spacing all through the bunch.

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CONCLUSIONS

As part of a collaboration we developed a tool capable of detecting and analyzing peaks in a variety of different spectra. The analysis performed either in fast or thorough mode give information about the quality of the spectra and offer a powerful diagnostics tool in investigating issues in the FEL. The code has been optimized for seeded FEL with a prominent emission mode but it could be adapted for SASE multimode case.

REFERENCES


