Reconstructing Space-Charge Distorted IPM Profiles with Machine Learning Algorithms

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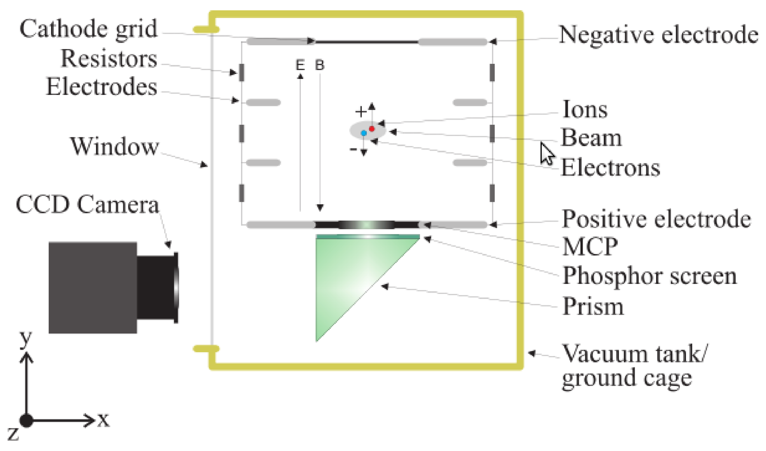
Abstract

Measurements of undistorted transverse profiles via Ionization Profile Monitors (IPMs) may pose a great challenge for high brightness or high energy beams due to interaction of ionized electrons or ions with the electromagnetic field of the beam. This contribution presents application of various machine learning algorithms to the problem of reconstructing the actual beam profile from measured profiles that are distorted by beam space-charge interaction. (Generalized) linear regression, artificial neural network and support vector machine algorithms are trained with simulation data, obtained from the Virtual-IPM simulation tool, in order to learn the relation between distorted profiles and original beam dimension. The performance of different algorithms is assessed and the obtained results are very promising for testing with simulation data.

IPM Working Principle



- Measure transverse beam profile
- Rest gas ionization during beam passage
- Ionization products are guided towards an acquisition system via electric field
- Optionally align magnetic field to confine electrons' trajectories

Simulation

Parameter	Values
Beam particle type	Protons
Energy/u	6.5 TeV
Bunch population	1.1×10^{11} ppb to 2.1×10^{11} ppb
Bunch length (4σ)	0.9 ns to 1.2 ns
Bunch width (1σ)	270 µm to 370 µm
Bunch height (1σ)	360 µm to 600 µm
Electrode distance	85 mm
Applied voltage	4 kV
Magnetic field	0.2 T
Simulated particle type	Electrons
Number of sim. particles	1 000 000
Time step size	0.3125 ps

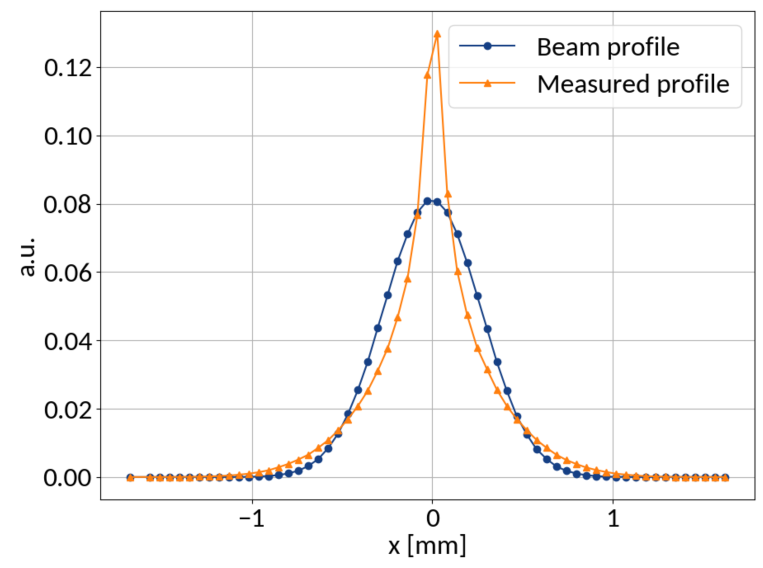
21,021 cases | 5h / case | 12 yrs

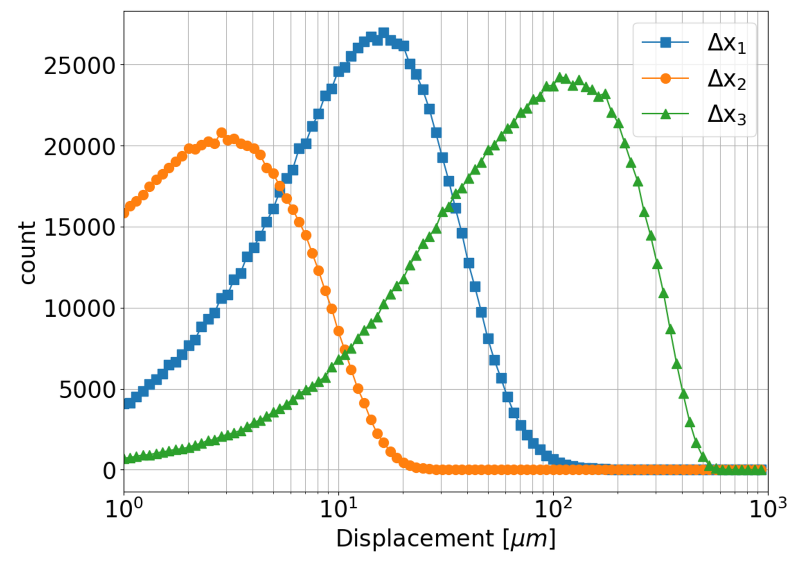
- Double differential cross section for generating initial velocities
- Analytic formula for transverse electric field of Gaussian charge distribution
- Uniform electric, magnetic guiding fields

https://gitlab.com/IPMsim/Virtual-IPM

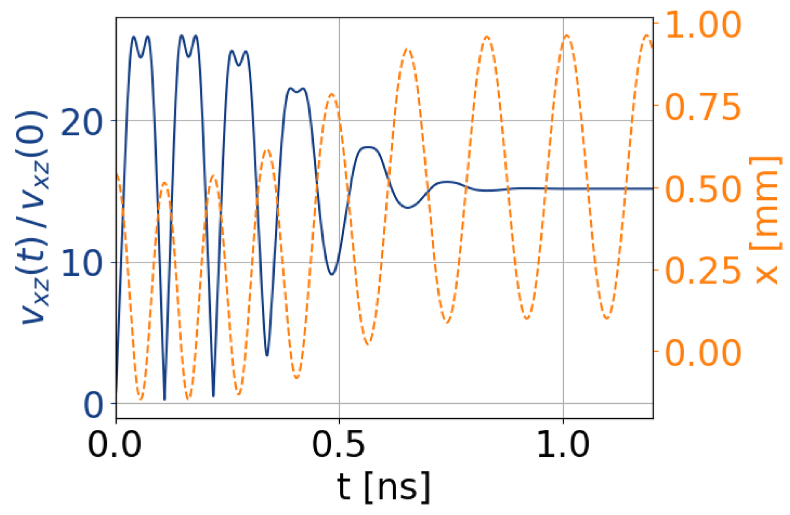
https://pypi.org/project/virtual-ipm

IPM Profile Distortion





- Electrons interact with the electric field of the particle beam
  → increase of gyroradius
  → increase of possible displacement
- Mainly three types of displ.:
  - Δx1: gyrocenter displ. due to initial velocity
  - Δx2: gyrocenter displ. due to space-charge interaction
  - Δx3: displ. due to gyromotion



Example trajectory showing the oscillation of position and velocity in the electric field of the beam.

Machine Learning

Multivariable Linear Regression

$$\sigma_x = \vec{\beta}^T \vec{x} + b + \epsilon$$

weights predictors intercept error

Kernel Ridge Regression

$$\sigma_x = \sum_k \alpha_k K\left(\vec{x}_k, \vec{x}\right) + b$$

$$K(x, y) = \varphi(x) \cdot \varphi(y)$$

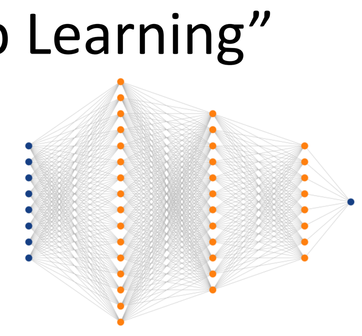
"Kernel trick" with transformation φ
→ linear dependence in dual space

Support Vector Machine Regression

$$\sigma_x = \sum_k \left(\alpha_k - \alpha_k^*\right) K\left(\vec{x}_k, \vec{x}\right) + b$$

Similar decision function as KRR but different loss function for determining the coefficients α

Multi-layer Perceptron, "Deep Learning"

$\vec{x} =$  $= \sigma_x$

Data Preprocessing

ppb	σz	f [0] ... f [n]	i [0] ... i[n]

Input variables (predictors)
→ Drop zero-variance predictors
→ Rescale (zero mean, unit variance)

Compute beam width = output variable (response)
→ Optionally rescale

Performance Scores

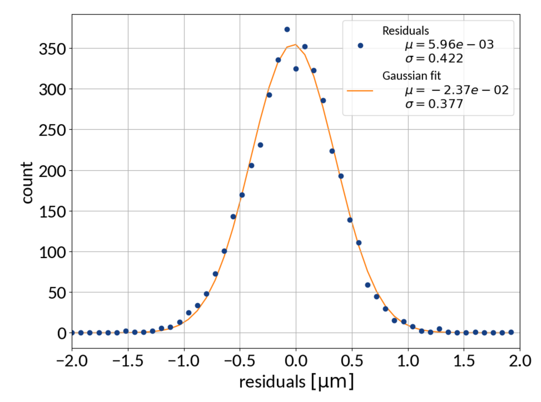
R2-score $1 - \frac{\sum_k \left(y_k - y_{p,k}\right)^2}{\sum_k \left(y_k - \mu\right)^2}$

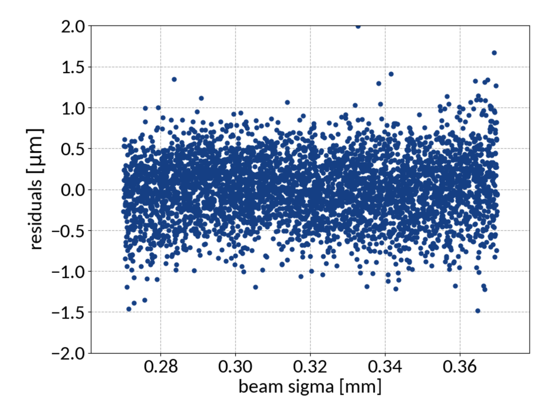
Explained Variance $1 - \frac{\mathrm{Var}\{y - y_p\}}{\mathrm{Var}\{y\}}$

Mean Squared Error $\frac{1}{N} \sum_k \left(y_k - y_{p,k}\right)^2$

Results with Simulation Data

	μ (res)	σ (res)	R2	EV	MSE
Linear	0.012	0.449	0.99976	0.99976	0.201
KRR	0.005	0.340	0.99986	0.99986	0.115
SVM	0.006	0.349	0.99985	0.99985	0.121
MLP	0.232	0.370	0.99977	0.99984	0.190



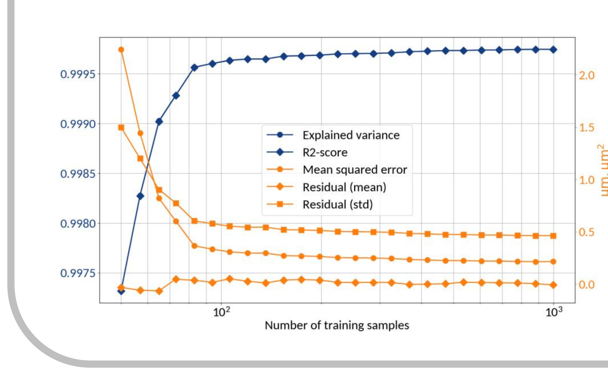


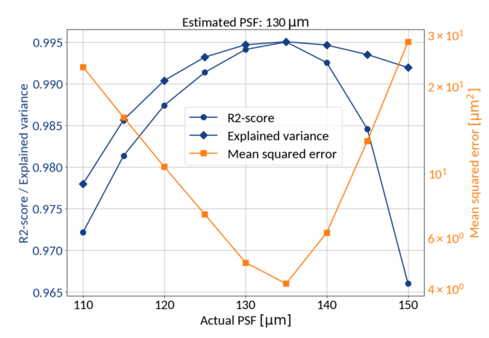
Performance on test data

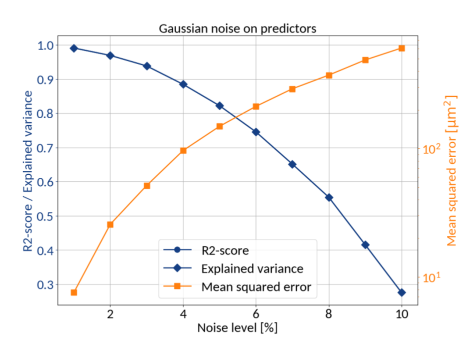
Kernel	R2	EV	MSE
RBF	0.99978	0.99978	0.178

Kernel ridge regression
$(\alpha = 10^{-3}, \gamma = 2 \cdot 10^{-4})$

- Various uncertainties might influence the quality of predictions
- Measurement errors, biased estimation for optical point-spread function, etc.







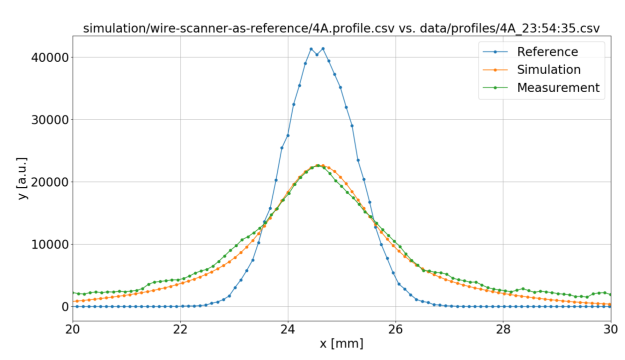
Next steps

- Hyper-parameter tuning and model selection can be tedious
- Tools for automating this process are available → opt for the best model

- Collect more measurement data for space-charge distorted IPM profiles
- Can be induced by using artificially small magnetic guiding fields (if tunable)

https://ipmsim.gitlab.io/IPMSim/measurements/

- Evaluate performance of ML models for measured data
- Performed at SPS IPMs (CERN), reference profile from Wire Scanners



Convoluted with 520µm PSF.