# Identification of Field Errors with Machine Learning Techniques 

Conrad Caliari

31.03.2022

Contact: c.caliari@gsi.de

## Outline

Field Errors
Identification with Machine Learning Techniques

Model Systematic Deviations

Measurement Systematic Deviations

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Field Errors

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## Field Errors

- unwanted multipoles
- excite resonances
- reduce dynamic aperture
- cause beam loss
- mitigation and correction
- compensation computable from accurate model
- requires type, location and strength
- dedicated beam time necessary to find them LOCO-algorithm, non-linear tune response
 matrix


## Accelerator Set Up



## Accelerator Set Up



SIS18 measurements
-> tunes show systematic shift
-> quadrupole error present in accelerator


## Accelerator Set Up



## Goal: Identify Field Errors

## Goal

- identify field errors from measurements
- support operation of accelerator
approach

1. compare measurements and predictions of accelerator model
2. quantify difference by loss $\mathcal{L}$
3. minimize $\mathcal{L}$ by varying multipole strengths of model
$\Rightarrow$ obtain accurate representation of accelerator
$\Rightarrow$ identify linear \& non-linear field errors

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## Loss

## loss $\mathcal{L}$

- quantify difference of trajectories
- measurements: observe motion of beam centroid with BPMs


$$
\mathcal{L}=\sum_{N_{\text {turns }}} \sum_{N_{\text {BPM }}}\left(\left.\frac{1}{\hat{\sigma}}\left[\begin{array}{l}
x  \tag{1}\\
y
\end{array}\right]\right|_{\text {measurement }}-\left.\frac{1}{\hat{\sigma}}\left[\begin{array}{l}
x \\
y
\end{array}\right]\right|_{\text {model }}\right)^{2}
$$

$\hat{\sigma}$ normalization factor $\propto \operatorname{var}(x), \operatorname{var}(y)$

## Accelerator Model

self-implemented tracking code with automatic differentiation

- based on drift-kick approximation, 6D tracking
- concatenation of differentiable maps
- enable differentiation of whole tracking model w.r.t. multipole strengths
- compute $\frac{\partial \mathcal{L}}{\partial k_{i, j}}$ with $k_{i, j} i$-th multipole of $j$-th magnet


## Accelerator Model

self-implemented tracking code with automatic differentiation

- based on drift-kick approximation, 6D tracking
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- compute $\frac{\partial \mathcal{L}}{\partial k_{i, j}}$ with $k_{i, j}$ i-th multipole of $j$-th magnet
- single particle tracking
- features
- exact drifts, no truncation
- transversal magnetic fields up to arbitrary order
- linearized dipole edges
- benchmarked against MAD-X, SixTrackLib


## Analogy to Artificial Neural Networks (ANNs)

similarities to artificial neural networks

- concatenation of simple, non-linear maps
- optimization of some scalar loss over training set
- large amount of tunable parameters
- well suited for automatic differentiation
- stochastic gradient descent
$\Rightarrow$ use gradient based algorithms designed to train ANNs
$\Rightarrow$ identify linear \& non-linear field errors


## Application to SIS18 in Simulations

## Presentation of Problem

goal: locate order \& strength of field error

- hide field errors in accelerator
- quadrupoles
- sextupoles
- octupoles
- training robust against additional deviations?
- finite integration order of magnets
- hide multipoles in accelerator not captured by training


## Application to SIS18 in Simulations

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- learning parameters
- $k_{1}, k_{2}, k_{3}$
- at two locations per cell $\Rightarrow 72$ free parameters
- training data set
- 18 trajectories for different initial conditions


## Application to SIS18 in Simulations

## Results





$$
\Rightarrow \text { no overfitting }
$$

$\Rightarrow$ resolution: quadrupole errors $\propto 10^{-7} \mathrm{~m}^{-2}$, sextupoles $\propto 10^{-6} \mathrm{~m}^{-3}$

## Application to SIS18 in Simulations

Overview

- successful identification of field errors in simulations
- possible to identify
- quadrupoles
- sextupoles
- octupoles


## Outline

```
Field Errors
Identification with Machine Learning Techniques
```

Model Systematic Deviations

## Measurement Systematic Deviations

## Steps Towards Application at Accelerators

steps towards training with measured data
model systematic deviations

1. resolution of multipoles?
2. effect of uncaptured non-linearities?
3. influence of working point?

## 1) Possible Resolution of Field Errors

symplectic integrator of finite order

- tradeof between accuracy and speed


$\Rightarrow$ possible to resolve field errors with sufficiently fast model


## 2) Effect of Additional Field Errors

training possible if additional unconsidered non-linearities present? train $k_{1}, k_{2}$, hide unconsidered octupole error in SIS18

$\Rightarrow$ unconsidered octupole: resolution still feasible

$$
\text { (errors in SIS18: } \Delta k_{1} \propto 5 \times 10^{-3} \mathrm{~m}^{-2}, \Delta k_{2} \propto 10^{-2} \mathrm{~m}^{-3} \text { ) }
$$

## 3) Influence Working Point on Training



$\Rightarrow$ no significant effect on quadrupole resolution
$\Rightarrow$ sextupole resolution accecptable for application to SIS18
(errors in SIS18: $\Delta k_{1} \propto 5 \times 10^{-3} \mathrm{~m}^{-2}, \Delta k_{2} \propto 10^{-2} \mathrm{~m}^{-3}$ )

## Outline

Field Errors<br>Identification with Machine Learning Techniques<br>Model Systematic Deviations<br>Measurement Systematic Deviations

## Steps Towards Application at Accelerators

steps towards training with measured data

## model systematic deviations

1. resolution of multipoles?
2. effect of uncaptured non-linearities?
3. influence of working point?
measurement systematic deviations
4. how to obtain initial condition from measurements?
5. represent centroid motion by single particle motion?
6. training possible with finite BPM resolution?

## 1) Recovery of Initial Condition

Hilbert Transform

model does particle tracking $\Rightarrow$ require initial condition get $x, y$ from BPMs, how to get $p_{x}, p_{y}$ ?

## 1) Recovery of Initial Condition

## Hilbert Transform

model does particle tracking $\Rightarrow$ require initial condition get $x, y$ from BPMs, how to get $p_{x}, p_{y}$ ?

Hilbert transform

- applies $\pm \frac{\pi}{2}$ phase shift to signals
- use to obtain transversal momenta in normalized phase space coordinates
- requires precise knowledge of twiss parameters



## 1) Recovery of Initial Condition

Leverage Kickers
model does particle tracking $\Rightarrow$ require initial condition get $x, y$ from BPMs, how to get $p_{x}, p_{y}$ ?

## Hilbert transform

- applies $\pm \frac{\pi}{2}$ phase shift to signals
- use to obtain transversal momenta in normalized phase space coordinates
- requires precise knowledge of twiss parameters
alternative: kick beam
- beam at rest

$$
\left[x, p_{x}, y, p_{y}\right]=[0,0,0,0]
$$

- kick beam $\rightarrow$ set momenta
- requires precise knowledge of kicker field


## 2) Effect of Decoherence on Training

How good can single-particle motion represent bunch motion?

- decoherence: particles oscillate with different tunes $\nu \Rightarrow$ beam debunches
- effect on training resolution?
- two mechanisms
- amplitude detuning: $\nu_{z} \rightarrow \nu_{z}\left(J_{z}\right)$ detuning $\propto \epsilon_{x}, \epsilon_{y}$
- chromatic detuning: $\nu_{z} \rightarrow \nu_{z}(\delta)$ detuning $\propto \sigma_{E}$


## 2) Effect of Decoherence on Training

How good can single-particle motion represent bunch motion?


difference in bunch motion and single particle motion after kick

## 2) Effect of Decoherence on Training



Figure: Resolution vs. geometric emittance.


Figure: Resolution vs. rms energy spread.
amplitude detuning (errors in SIS18: $\Delta k_{1} \propto 5 \times 10^{-3} \mathrm{~m}^{-2}, \Delta k_{2} \propto 10^{-2} \mathrm{~m}^{-3}$ )

## 3) Resolve Influence of Multipoles with BPMs

How much does centroid motion change over 3 turns?
kick beam and track centroid with / without field error


resolution of BPMs $\sim 10 \mu \mathrm{~m}$
$\Rightarrow$ resolve influence of gradient errors
$\Rightarrow$ effect of sextupole errors close to BPM resolution

## Conclusion

successful identification of field errors in simulations

- quadrupole, sextupole, octupole
- robust against
- uncaptured non-linearities
- chosen working point
- finite integration order of magnets
- convergence affirmed by multitude of simulations
- no overfitting


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successful identification of field errors in simulations

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training on real measurement data
- control initial conditions by kickers
- require 18 shots of synchrotron to create training data set
- representation of bunch centroid by single particle
- resolution of multipoles affected
- finite resolution of BPMs
- identify gradient errors in SIS18
- sextupole errors close to resolution limit


## End

Thank you for your attention!

References I

## Training Set



- ground truth to be fitted by model
- kick beam horizontally \& vertically
- typical size of train set: 18 trajectories


## Detuning in presence of Exact Drifts

- study detuning caused by exact drifts
- compare motion of beam centroid to centroid particle
- beam parameters
- geo. emittance $\epsilon_{x}=\epsilon_{y}=34 \mu \mathrm{~m}$
- monoenergetic beam, $\sigma_{E}=0$

(a) Linear lattice with exact drifts.

(b) Linear lattice with linear drifts.

