## Distributed Matching Scheme and a Flexible Deterministic Matching Algorithm for Arbitrary Systems IPAC 2016, Busan, Korea

Yu-Chiu Chao May 9th, 2016

## Exploring Alternative Approaches to Matching

*Performance Improvements through Distributed Matching
$>$ Envelope and Jitter Control Not Limited by Geographical Location
$>$ Avoiding Beam Blowup \& Optical Sensitivity Due to Drastic Matching
$>$ Improving Error Tolerance \& Dynamic Correction Capability
A New Approach to Matching Algorithm
$>$ Robustness and Determinism
$>$ Logic and Insight
$>$ Flexibility and Control
$>$ Solution Capability - Less Vulnerable to Optics/System Complexity

* Advantages through Operational Implementation
$>$ Pre-Computed Matching Solutions
$>$ Speed - Major Computation Done Offline
$>$ User Control and Options

Motivation for Distributed Matching

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## Motivation for Distributed Matching



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$30^{\circ}$ FODO

Lattice
Design $\beta_{\mathrm{X} / \mathbf{Y}}$
Mismatched


Motivation for Distributed Matching


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Distributed Matching over 7.5 cells at source

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$\delta \mathrm{M}_{21}(1 / \mathrm{m})$

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Blowup averted
Matching failure dynamically corrected
Baseline optics minimally perturbed

## Two Schemes of Accelerator Control Configuration

* Localized Control
$>$ Limited/Costly/Bulky monitor \& actuator
> Little cumulative/compounded error
$>$ Damage is mostly localized
$>$ Example: Dispersion, $\sigma_{\mathrm{L}}$, Energy, $\sigma_{\mathrm{E}} \ldots .>$ Example: Transverse orbit Transverse Matching (Beam \&Transport) Fits the Distributed Model Better, But....

Traditionally It Acquired a Local Flavor in Design \& Operation.

* A legacy deserving revisit: Without adequate monitoring, competent global algorithm, and real time computing power, this was understandable.
* Not unlike global steering by correctors before these ingredients were in place. Aversion to Chaos largely responsible for traditional Local Matching Paradigm $\Rightarrow 100 \%$ matching within dedicated section; Other quads passively hold up transport.
$>$ Dedicated matching sections are required - Extra constraint on design \& operation
$>$ Long range cumulative error; Drastic correction; Local blowup, Solution difficulty.
$>$ No recourse to matching failure; No error tolerance; No dynamic correction.
$>$ And: Large beam envelope/jitter can sample nonlinearities in irreversible ways. The Message:
$>$ Primary role of quads is Envelope/Jitter containment, better actively than passively.
$>$ It's not about whether, but how to use all quads for matching in an intelligent way.


## Optimization $\Rightarrow$ Optimized Trade-Off $-\left(2^{\text {nd }}\right)$ Alternate View

* Distributed Matching $\Rightarrow$ Partially Matched Solutions
$\Rightarrow$ Degeneracy $\Rightarrow$ Require Further Constraints to Produce Unique Answer
* Matching is never single-objective at the cost to all else (e.g. Quad Strength) $\Rightarrow$ Needs Rigorous Framework for Trade-Off between Competing Objectives Lagrange Multiplier Formulation
Variables: $\quad k_{1}, k_{2}, \ldots k_{N}$
Objective 1: $\boldsymbol{F}\left(k_{1}, k_{2}, \ldots k_{N}\right)$
Objective 2: $\boldsymbol{H}\left(k_{1}, k_{2}, \ldots k_{N}\right)$



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Objective 1: $F=\Phi$
Generalized 4D mismatch factor

$$
\boldsymbol{F}=\Phi=\frac{1}{4} \operatorname{Tr}\left(\Sigma_{D}^{-1} \cdot M\left(k_{m}\right) \cdot \Sigma_{R} \cdot M^{T}\left(k_{m}\right)\right) \geq 1
$$

R: Actual
Objective 2: $\boldsymbol{H}=\Delta \mathbb{K}$ : RMS Quad deviation off design

$$
\boldsymbol{H}=\Delta \mathrm{K}=\sum_{m=1}^{N_{Q}}\left(k_{m}^{R}-k_{m}^{D}\right)^{2}=\sum_{k=1}^{N_{Q}} \delta k_{m}^{2} \geq 0
$$

D: $\mathrm{Design}_{5}$

## RECIPE

Starting point $\left(\Delta \mathrm{K}=0, \Phi=\Phi_{0}\right)$ :

$$
\begin{aligned}
\boldsymbol{\mu}=0 ; \quad \boldsymbol{k}_{\boldsymbol{i}}=\mathbf{0} \\
\left.\frac{d \boldsymbol{k}_{\boldsymbol{i}}}{d \mu}\right|_{\mu=0}=\left.\frac{1}{2} \frac{\partial F(\boldsymbol{k})}{\partial k_{\boldsymbol{i}}}\right|_{k_{m}=0}
\end{aligned}
$$

Evolution of $\boldsymbol{k}_{\boldsymbol{i}}(\lambda=1 / \mu)$ :


$$
\frac{d \boldsymbol{k}}{d \boldsymbol{f}}\left|=\frac{1}{\lambda} \cdot \frac{\operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}}{\boldsymbol{R}^{T} \cdot \operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}}, \quad \frac{d \boldsymbol{k}}{d \boldsymbol{h}}\right|=\frac{\operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}}{\boldsymbol{R}^{T} \cdot \operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}} \quad \boldsymbol{R}^{T} \cdot \operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R} \neq 0
$$

$$
\frac{d \boldsymbol{k}}{d \lambda}\left|=\boldsymbol{M}^{-1} \cdot \boldsymbol{R}, \quad \frac{d \boldsymbol{k}}{d \mu}\right|=\boldsymbol{N}^{-1} \cdot \boldsymbol{S} \quad \operatorname{Det}(\boldsymbol{M}) \neq 0
$$

$$
\boldsymbol{M}_{i j}=\frac{\partial^{2}(F(\boldsymbol{k})-\lambda \cdot H(\boldsymbol{k}))}{\partial k_{i} \partial k_{j}}, \quad \boldsymbol{R}_{\boldsymbol{i}}=\frac{\partial H(\boldsymbol{k})}{\partial k_{\boldsymbol{i}}}
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Evolution of Quad $\boldsymbol{k}_{\boldsymbol{i}}$

Evolution of $\lambda \& \mu=1 / \lambda$ vs $\Phi$


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$$

Evolution of

Evolution
Quad $\boldsymbol{k}_{i}$

Evolution of $\lambda \& \mu=1 / \lambda$ vs $\Phi$


* End Point (Optimally Matched): $\lambda=0$

Evolution of $\boldsymbol{k}_{\boldsymbol{i}}(\lambda=1 / \mu)$ :

## More Robust Formulation (Singularity Free)

* Tailored to a Runge-Kutta type process with only local derivatives defined.

| Start/Stop | Integration Formula | Evolution of Competing Objectives |
| :--- | :--- | :--- |
| $0>\mu>-1$ | $\frac{d \boldsymbol{k}}{d k}= \pm \widehat{\boldsymbol{Q}}, \quad \boldsymbol{Q}=\operatorname{Adj}(\boldsymbol{N}) \cdot \boldsymbol{S}$ | $\frac{d f}{d k}= \pm \frac{\left(\boldsymbol{S}^{T} \cdot \operatorname{Adj}(\boldsymbol{N}) \cdot \boldsymbol{S}\right)}{\|\boldsymbol{Q}\|}= \pm \boldsymbol{S}^{T} \cdot \widehat{\boldsymbol{Q}}$ |
|  | $\frac{d \mu}{d k}= \pm \frac{\operatorname{Det}(\boldsymbol{N})}{\|\boldsymbol{Q}\|}$ | $\frac{d h}{d k}= \pm \frac{\mu \cdot\left(\boldsymbol{S}^{T} \cdot \operatorname{Adj}(\boldsymbol{N}) \cdot \boldsymbol{S}\right)}{\|\boldsymbol{Q}\|}= \pm \mu \cdot \boldsymbol{S}^{T} \cdot \widehat{\boldsymbol{Q}}$ |

$$
\begin{array}{ll}
\boldsymbol{M}_{i j}=\frac{\partial^{2}(F(\boldsymbol{k})-\lambda \cdot H(\boldsymbol{k}))}{\partial k_{i} \partial k_{j}}, & \boldsymbol{R}_{\boldsymbol{i}}=\frac{\partial H(\boldsymbol{k})}{\partial k_{i}} \\
\boldsymbol{N}_{i j}=\frac{\partial^{2}(H(\boldsymbol{k})-\mu \cdot F(\boldsymbol{k}))}{\partial k_{i} \partial k_{j}}, & \boldsymbol{S}_{i}=\frac{\partial F(\boldsymbol{k})}{\partial k_{i}}
\end{array}
$$

with no adverse effects.


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| $0>\mu>-1$ | $\begin{aligned} & \frac{d k}{d k}= \pm \widehat{Q}, \quad Q=\operatorname{Adj}(N) \cdot S \\ & \frac{d \mu}{d k}= \pm \frac{\operatorname{Det}(N)}{\|Q\|} \end{aligned}$ | $\begin{aligned} & \frac{d f}{d k}= \pm \frac{\left(\boldsymbol{S}^{T} \cdot \operatorname{Adj}(\boldsymbol{N}) \cdot \boldsymbol{S}\right)}{\|\boldsymbol{Q}\|}= \pm S^{T} \cdot \widehat{\boldsymbol{Q}} \\ & \frac{d h}{d k}= \pm \frac{\mu \cdot\left(\boldsymbol{S}^{T} \cdot \operatorname{Adj}(\boldsymbol{N}) \cdot \boldsymbol{S}\right)}{\|\boldsymbol{Q}\|}= \pm \mu \cdot \boldsymbol{S}^{T} \cdot \hat{\mathbf{Q}} \end{aligned}$ |
| $-1<\lambda<0$ | $\begin{aligned} & \frac{d k}{d k}= \pm \widehat{P}, \quad P=\operatorname{Adj}(\boldsymbol{M}) \cdot R \\ & \frac{d \lambda}{d k}= \pm \frac{\operatorname{Det}(\boldsymbol{M})}{\|\boldsymbol{P}\|} \end{aligned}$ | $\begin{aligned} & \frac{d f}{d k}= \pm \frac{\left.\lambda \cdot \boldsymbol{R}^{T} \cdot \operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}\right)}{\|\boldsymbol{P}\|}= \pm \lambda \cdot \boldsymbol{R}^{T} \cdot \widehat{\boldsymbol{P}} \\ & \frac{d h}{d k}= \pm \frac{\left(\boldsymbol{R}^{T} \cdot \operatorname{Adj}(\boldsymbol{M}) \cdot \boldsymbol{R}\right)}{\|\boldsymbol{P}\|}= \pm \boldsymbol{R}^{T} \cdot \widehat{\boldsymbol{P}} \end{aligned}$ |

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\begin{array}{ll}
M_{i j}=\frac{\partial^{2}(F(\boldsymbol{k})-\lambda \cdot H(\boldsymbol{k}))}{\partial k_{i} \partial k_{j}}, & R_{i}=\frac{\partial H(\boldsymbol{k})}{\partial k_{i}} \\
N_{i j}=\frac{\partial^{2}(H(\boldsymbol{k})-\mu \cdot F(\boldsymbol{k}))}{\partial k_{i} \partial k_{j}}, & s_{i}=\frac{\partial F(\boldsymbol{k})}{\partial k_{i}} \\
\hline
\end{array}
$$



## Determinism - What Makes This Algorithm Unique

* Deterministic Start-of-Procedure
$>$ User defined starting $\boldsymbol{k}_{\boldsymbol{i}}$ (e.g. $\Delta \boldsymbol{k}_{\boldsymbol{i}}=0$, and $\boldsymbol{d} \boldsymbol{k}_{\boldsymbol{i}} / \boldsymbol{d} \boldsymbol{\mu}$ accordingly)
$>$ No "inspired guesses" for initial value
> No random number search
$>$ No case-by-case parameter tweaking to "guide" the solution
* Deterministic End-of-Procedure
A. If $\boldsymbol{\lambda}=\mathbf{0}$, Stop. (Best matching when $\Phi=1$ is not rigorously possible)
B. If $\boldsymbol{\lambda} \neq \mathbf{0}$, Don't stop. (Big gain by insisting on $\boldsymbol{\lambda}=0$ even when $\Phi \cong 1$ )
$>$ Both are less trivial than appear
$>$ Conventional algorithm: Ambivalent about $\mathbf{A}$, and can stop short of $\mathbf{B}$ and $\underline{\text { miss significant payoff. (Example to follow) }}$

A Solution is Guaranteed, Plus
$>$ Guaranteed Global optimum for all intermediate solutions
$>$ Entire range of intermediate optimal solutions between $\mu=0$ and $\lambda=0$

## More Advantages

$>$ Works on any system, including XYcoupled and interspersed modules

$>$ Computational demand is a slow function of optics/system complexity

## Try Solving $\nabla \Phi=0$ for 5 Quads

$>$ Systematic procedure to map out and isolate Global optimum (Pareto Front)
$>$ Complete range of options for optimal

Design vs Actual X Phase Space trade-off (Ideal for distributed matching)

$\Delta K$ vs $\Phi$


Design vs Actual Y Phase

$$
=7254.6033
$$



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Quad K1-6 RMS $=0.019959500$
$\Delta \mathrm{K}$ vs $\Phi$



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Quad K1-6 RMS $=0.18171344$






$\Delta K$ vs $\Phi$


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Points of diminished return identified by well-defined procedure $(\operatorname{Det}(M)=0)$



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Quad K1-6
 well-defined procedure $(\operatorname{Det}(M)=0)$
$>$ Not dealing with a black box
$>$ Determinism, Robustness and Reproducibility are important for feedback applications

Each One A Serious Challenge to Conventional Methods trade-off (Ideal for distributed matching)
$>$ Points of diminished return identified by


# Implementing Distributed Matching Profile and Transport 

## Implementing Distributed Matching Profile and Transport



* Subdivide line into matching sections


## Implementing Distributed Matching Profile and Transport



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## Implementing Distributed Matching Profile and Transport



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## Implementing Distributed Matching Profile and Transport



* Subdivide line into matching sections $>$ Matching target for each section is Fixed


## Implementing Distributed Matching Profile and Transport

* To Fix Beam Profile Mismatch
$\Phi_{1}$

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## Implementing Distributed Matching Profile and Transport

* To Fix Beam Profile Mismatch

Best Partial


* Subdivide line into matching sections $>$ Matching target for each section is Fixed
* To Fix Optics/Transport Error


$$
\begin{aligned}
& \beta_{D}^{A} \cdot X^{\prime 2}+2 \alpha^{A}{ }_{D} \cdot X \cdot X^{\prime}+\gamma_{D}^{A} \cdot X^{2} \\
& \neq \beta^{B}{ }_{D} \cdot X^{\prime 2}+2 \alpha^{B}{ }_{D} \cdot X \cdot X^{\prime}+\gamma_{D}^{B} \cdot X^{2}
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CS invariant

## Implementing Distributed Matching Profile and Transport

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Match after error

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- CS invariant



## Implementing Distributed Matching Profile and Transport

* To Fix Beam Profile Mismatch

Best Partial


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Split difference

## Implementing Distributed Matching Profile and Transport

* To Fix Beam Profile Mismatch


Decide on tapered solution


$$
\sum^{D_{N}}
$$

* Subdivide line into matching sections $>$ Matching target for each section is Fixed
* To Fix Optics/Transport Error


Split difference
User has freedom on solution scenario, e.g. How to taper mismatch profile

## Why Perform Matching on Beam Time? - (3rd) Alternate View

Matching targets are fixed $\Rightarrow$ Pre-compute trade-off solutions Offline

* As functions of input mismatch and embedded modules (e.g. RF phase)
* During Online operation simply interpolate from Offline results.
$>$ Speed \& Predictability
Example (3-quad section $120^{\circ}$ FODO):
* Construct interpolation table covering range:
$>$ Input Mismatch Amp. $\Phi_{\mathrm{X} / \mathrm{Y}}=1 \rightarrow 9$
$>$ Input Mismatch Angle $\Theta_{X / Y}=0 \rightarrow \pi$
* Launch beam with initial mismatch:

$$
\begin{aligned}
& \Phi_{\mathrm{X} / \mathrm{Y}}=9 \\
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Evolution of beam through successive matching



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* Interpolate for partial matching in subsequent sections.

Normalized Design Beam Mismatched Beam $\Lambda=\sqrt{\Phi+\sqrt{\Phi^{2}-1}}$


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Section 5


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* During Online operation simply interpolate from Offline results.
$>$ Speed \& Predictability


## Example (3-quad section $120^{\circ}$ FODO):

* Construct interpolation table covering range:
$>$ Input Mismatch Amp. $\Phi_{\mathrm{X} / \mathrm{Y}}=1 \rightarrow 9$
$>$ Input Mismatch Angle $\Theta_{X / Y}=0 \rightarrow \pi$
* Launch beam with initial mismatch:

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* Interpolate for partial matching in subsequent sections.

Normalized Design Beam Mismatched Beam $\Lambda=\sqrt{\Phi+\sqrt{\Phi^{2}-1}}$


Evolution of beam through successive matching



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Determinism in algorithm is crucial to generating Massive interpolation tables!

Evolution of beam through successive matching


## Recap

* Possibility to Realize 3 Alternate Views to Matching
$>$ Distributed instead of Local
$>$ Optimizing Tradeoff Deterministically instead of Single objective
$>$ Offline Computation instead of Online
* Interlinked Concepts But Do Not Require Monolithic Implementation
$>$ Enabling component is stand-alone Matching Engine.
$>$ Distributed Scheme
> Interpolated Solution
* Application Beyond Matching
$>$ Works on any parameter with well-behaved analytic model
$>$ Determinism can be maintained even when starting point is not known a priori
$\Rightarrow$ (Impose Artificial Constraint) Input / Idea of Application Welcome!



## If $\lambda \neq 0$, Don’t Stop

* $30^{\circ}$ FODO; 6 Quad Matching;




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| $\Phi$ | 1.00013 | 1.0076 |
| :--- | :--- | :--- |
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Why Bother with $10^{-4}$ ?


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## $\Delta K$ Gain of $>\mathbf{5 0 \%}$

 By insisting on $\lambda \rightarrow 0$

| $\Phi$ | $\lambda$ | $\Delta \mathrm{K}$ |
| :---: | :---: | :---: |
| 1.00013 | -0.74 | 0.008 |
| 1.0076 | -2.42 | 0.005 |
| 1 | 0 | 0.003 |



Entire Path $\Rightarrow$ Local vs Global Optimum

* Local optimal condition is satisfied everywhere, but only some are "Global".
* Isolate global optima by short-circuiting inferior local optima.
$>$ Green curve is always monotonic $(\lambda<0)$ Akin to "Pareto Front" concept in multiobjective optimization



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$120^{\circ}$ FODO; 4 Quad Matching Section;




$>$ This 4-Quad Mismatched Configuration Does Not Allow 100\% Matching (All Roots Are Complex).
> Conventional Algorithm Cannot Give Unequivocal Answer Like This.



4-Quad Matching with No Real Roots
Y. Chao PAC 2001

## Application beyond Matching? - Restoring Determinism

* Algorithm should work on any other function with an analytical model.
* Determinism depends on "known" starting point. ( $\nabla \boldsymbol{H}=0, \Delta \boldsymbol{k}_{\boldsymbol{m}}=0$ or $\boldsymbol{k}_{\boldsymbol{m}}=0$ ) * What if neither $\nabla F=0$ nor $\nabla G=0$ is known a priori? Determinism Lost?



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Example of other possible objectives/constraints: (?)

$\Rightarrow \begin{aligned} & \text { Beam size at location inside } \\ & \text { matching section }\end{aligned}$
$>$ Total phase advance
$>$ Weighted mismatch $\Phi$,
> Absolute quad strengths
$>$ Weighted quad strengths (well defined meaning)
$>$ Maximizing mismatch $\Phi(\lambda>0)$
$>$ Transfer matrix elements
> Special module parameter (e.g., residual dispersion)
$>$ Higher order effects
$>$ Geometric parameters (e.g. Length)
$>$ Quad strings
$>$ Optical functions (e.g., dispersion, chromaticity, ....)


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* Possibility to Realize 3 Alternate Views to Matching
$>$ Distributed instead of Local
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* Interlinked Concepts - But Not a Monolithic Program to Implement
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Stand-Alone Matching Engine

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- Speed
- Predictability
- Reproducibility
- All algorithmic advantages


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$\lambda \operatorname{vs} \Phi$<br>

$\lambda$ vs $\Delta K$

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