Bayesian Structural Field Analysis of Large Eddy Turbulent Flow Simulation Using Probabilistic Graphical Modeling

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Motivation: Preamble

- Commander: If I am to invest in BBN software, demonstrate to me what it can do for me first.

1) **State Estimation** - How can it help me **characterize** adversarial behavior?

2) **Optimal Learning** - How can it help me **decide** on what to do based on known goals?

- Request: Use easily understandable models!

- Answer: Use **Crowd Turbulence - Fluid Turbulence Analogy**

Outline

1) **Introduction:** Traditional Geo-Intelligence Problems

2) **DPF System Characterization**
   A) Why use DPF for system characterization?
   B) Why use DPF data for system modeling?
   C) Image Particle Dynamics Phenomenology

3) **Modeling Methodology**
   A) Global Two-Tier Processing
   i) Feature Extraction
   ii) Hidden Markov Model Parameter Learning

   B) Physical Interpretation of Emission Matrices

   C) Knowledge Gradient Policy Information Ranking

4) **Conclusions**

Introduction: Traditional Geo-Intelligence Problems

1) Military geo-intelligence electro-optical remote sensing platforms are often tasked with monitoring complex (including human) systems which **change over time**

   a) **Navy**: Radar remote sensing of riverine and ocean waters for underwater **mine detection**

   b) **Air Force**: Multidimensional imagery remote sensing of land processes for comprehending **adversarial motion**

   c) **Homeland Security:** Panchromatic remote sensing of **crowd turbulence** for adversarial surveillance

2) Traditionally, linear **optimal Bayesian estimators** have been used as state estimators to address these sorts of problems

Why use DPF for System Characterization?

- Real world systems = highly **nonlinear** and **probabilistic**
- Knowledge of the dynamical system model does **not** exist
- State estimation initially requires **model learning** or **system characterization**
- Dynamic particle fields (DPF) obtained from large eddy simulations (LES)

Optimal **temporal-based Bayesian system characterization**

- **Parameterized system model** aids in **future state assessment** and decision making

Why use DPF Data for System Modeling?

- Turbulent particle fields have strong similitude to both **marine** and **human many-body** systems of military interest

- DPF equations emanate from **turbulent fluid mechanics**

- DPF data possesses **both** particle **imagery motion** and the underlying **driving force** behind the motion

- **Both** variables necessary for robust probabilistic **system modeling**
- **Not readily available in open source data sets**

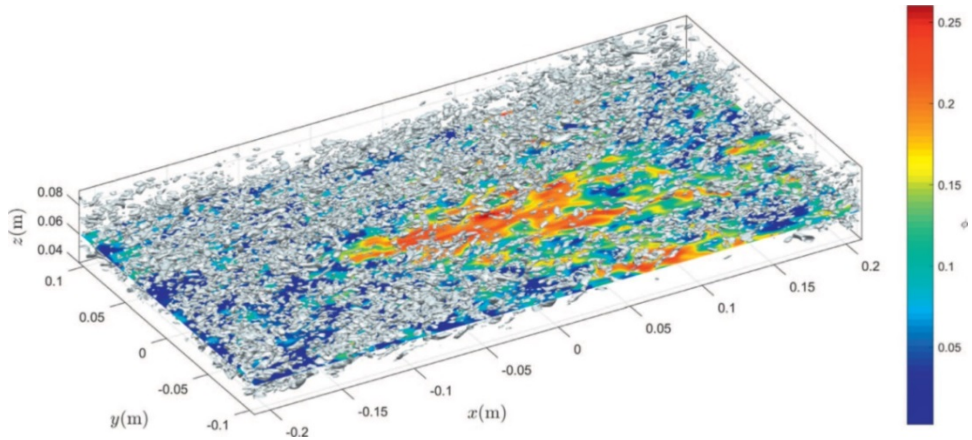
- DPF data = **noiseless and seemingly random**

  allows for **pure algorithmic exploration**

DPF System Characterization:
Imaged Particle Dynamics Phenomenology

1) Dynamic particles = point tracers *representing* different phenomena
(E.g. people or objects)

2) Modeling point: Though ***seemingly*** random and unpredictable, statistical structure exists as particles move through space/time.



3) Particle patterns emerge as particles **coagulate** into groups and **disperse**

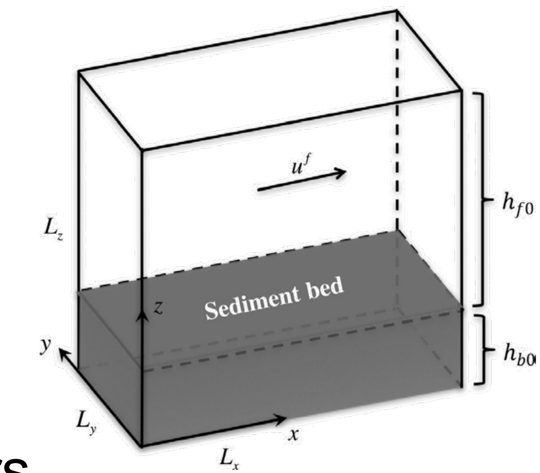
4) DPF dynamics mimics how **chaotic state** of geo-intelligence processes **with an organized or pattern-like** quality

E.g. Organized adversarial motion, coherent wakes cause by mines

Modeling Methodology: Two Tier Processing

- Objective of DPF data **system modeling:** to employ **machine learning algorithms** to create a probabilistic graphical model

- DPF data processing employs **two tiers**



A) Feature Extraction

- Data domain split horizontally into 2 layers
- Each **dimensionally reduced** to **single values**

- **Bottom layer** -> characteristic latent causal **states**
  Top layer -> characteristic surface particle **observations**

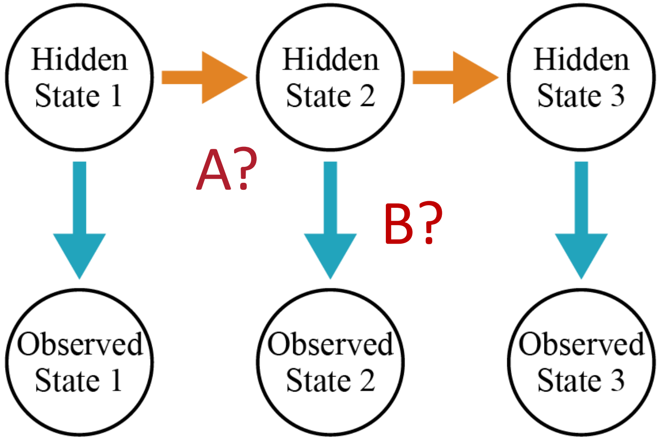
Modeling Methodology: Two Tier Processing

B) Hidden Markov (Bayesian) Model Parameter Learning

Statistical relationship between **observations (upper layer structure)** and **states (bottom layer structure)** can be **learned!**

Assumptions?

1) State- Markovian
2) Observations - independent



- **Instance counting** can be used to estimate the **transition probabilities, A and emission probabilities, B**

- Parameterized HMM allows for **system characterization** of relationship between surface and bottom

Feature Extraction from DPF Data

Global Methodology:

1) Decompose surface and sub-surface DPF using **feature extraction**

Machine ⇓ Learning

2) 9-D Feature time series array of surface and subsurface values!

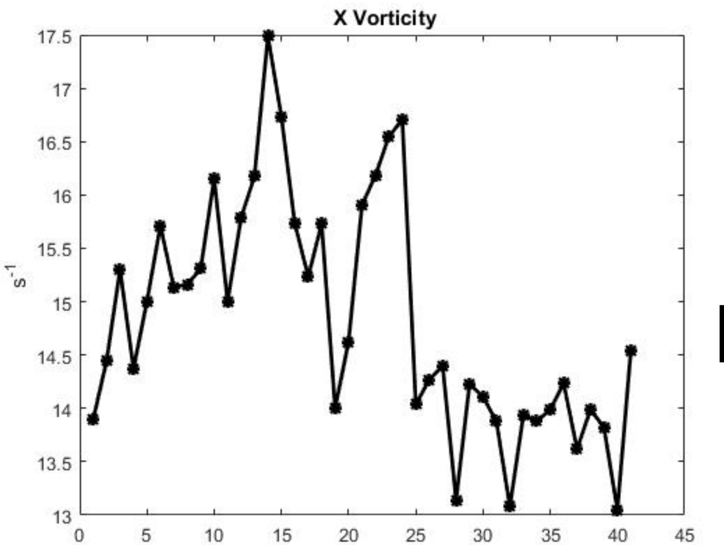
7 Surface Features (Effects)

- **a) Cross flow spatial scale**
- **b) Characteristic PCA based Concentration spatial scale**
- **c) Characteristic PCA based W velocity spatial scale**
- **d) Characteristics ICA based Concentration spatial scale**
- **e) RMS PCA based V velocity**
- **f) RMS PCA based W velocity**
- **g) RMS PCA based concentration**

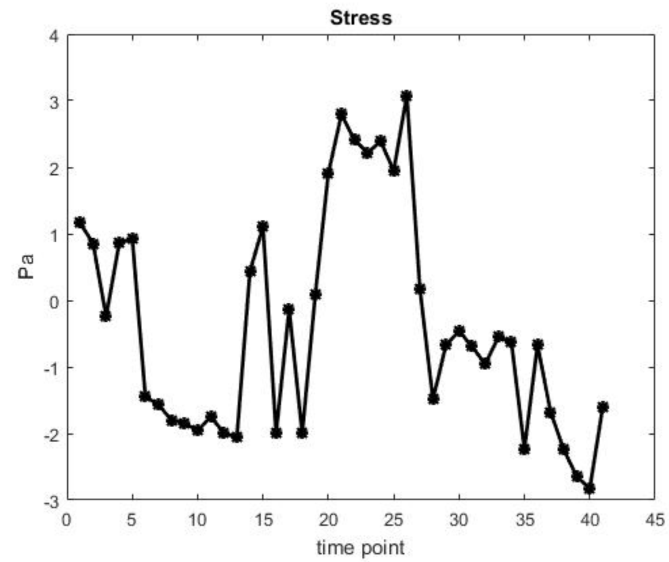
2 Sub-surface (Cause)

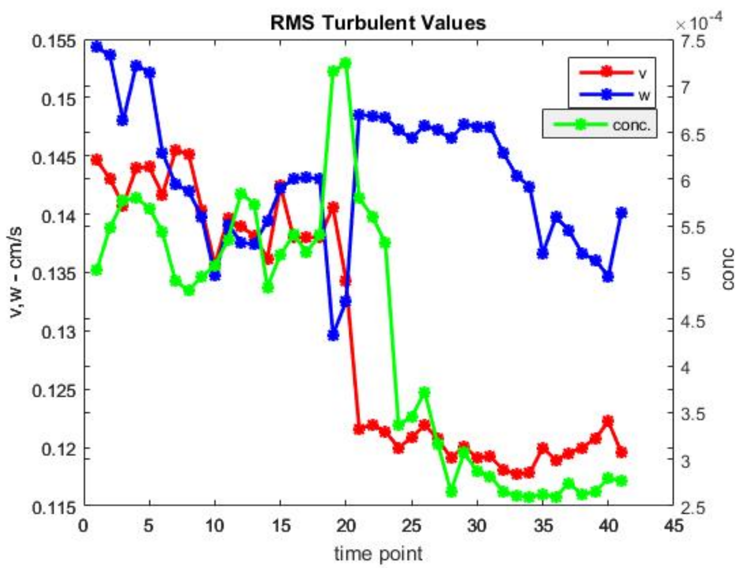
- **a) Vorticity**
- **b) Stress**

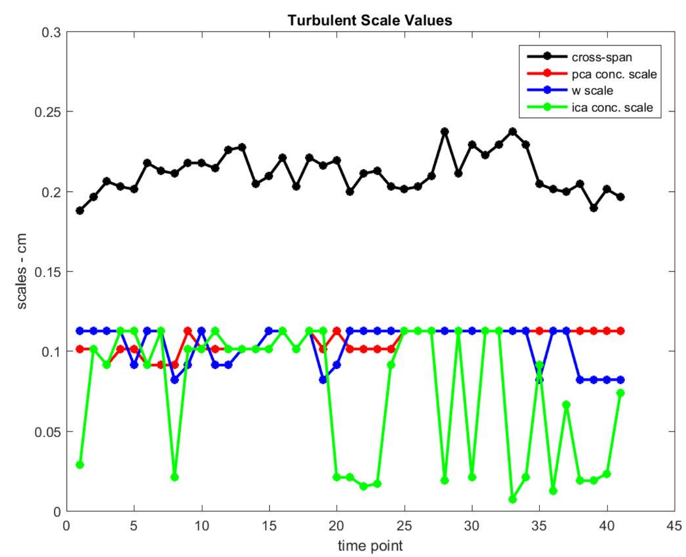
Sub-surface and Surface Feature Time Series



Data Paucity!





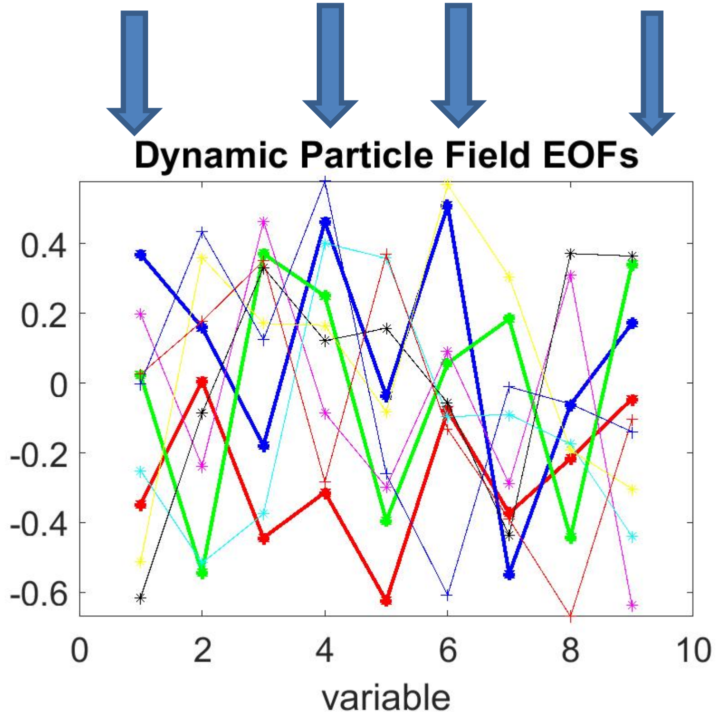


Feature Extraction from DPF Data

Global Methodology:

3) Perform **EOF analysis** to determine worthy candidates for HMM parameter estimation.

Choose surface and sub-surface variable subset



a) Vorticity (cause)
b) RMS PCA based V velocity (effect)
c) RMS PCA based concentration (effect)
d) ICA based concentration scales (effect)

9 -> 4 Features

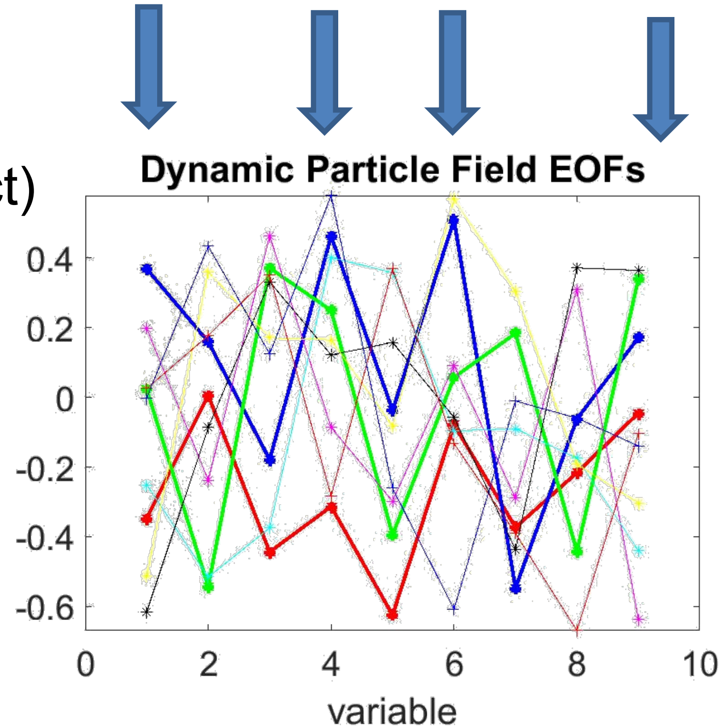
Hidden Markov Model Parameter Learning

Global Methodology:

3) Perform EOF analysis to determine worthy candidates for HMM parameter estimation. Choose surface and sub-surface variable subset

a) Vorticity (cause)
b) RMS PCA based V velocity (effect)
c) RMS PCA based concentration (effect)
d) ICA based concentration scales (effect)

4) **Use 4 features in HMM parameter estimation to estimate transition and emission matrices (1 cause, 3 effects)**



Physical Interpretation of Emission Matrix 1
Vorticity and RMS V Velocity

	Low rms v velocity 0.115 – 0.125 (m/s)	Medium rms v velocity 0.125 – 0.14 (m/s)	High rms v velocity 0.14 – 0.15 (m/s)
Low vorticity 13.0 – 14.5 (s^{-1})	0.6000	0	0.4000
Medium vorticity 14.5 – 16.0 (s^{-1})	0.0769	0.4615	0.4615
High vorticity 16.0 – 17.5 (s^{-1})	0.4286	0.4286	0.1429

Vorticity and RMS V Velocity are close **dynamic cousins**!
We expect strict **proportionality**.

Physical Interpretation of Emission Matrix 1
Vorticity and RMS V Velocity

- **Complex** emission matrix due to **non-linearity relationship** between vorticity and rms surface v velocity

Low vorticity 13.0 – 14.5 (s^{-1})	Low vel. 0.6000	Medium vel. 0	Large vel. 0.4000

- At low vorticity levels -> low rms v vel. (60%) **AND high rms v vel.(40%)**

Q: Why? **A: Flow nonlinearity**

- Low vorticity (cause) -> low stress (effect)
  -> low sediment injection into the water column
  -> flow field 'adjusts' to sediment modulation
  -> turbulent fluctuations increase

- Low vorticity levels -> high rms v turbulent vel.

Physical Interpretation of Emission Matrix 1
Vorticity and RMS V Velocity

- At medium vorticity levels -> strong % at medium and high rms v velocity levels
- At high vorticity levels -> strong % at medium and **low rms v velocity levels**
- **Q : Why?**

High vorticity 16.0 – 17.5 (s^{-1})	Low vel.	Medium vel.	High vel.
	0.4286	0.4286	0.1429

- A: High vorticity levels -> sediment flux to the surface boundary layer
  -> **dampens surface v velocity**

High vorticity levels -> low rms v velocity

Physical Interpretation of Emission Matrix 3
Vorticity and Sediment Concentration Spatial Scales

	Small Conc. Scales 0 – 0.08 (cm)	Medium Conc. Scales 0.08 – 0.11 (cm)	Large Conc. Scales 0.11 – 0.12 (cm)
Low Vorticity 13.0 – 14.5 (s^{-1})	0.5	0.1000	0.4000
Medium Vorticity 14.5 – 16.0 (s^{-1})	0.2857	0.3571	0.3571
High Vorticity 16.0 – 17.5 (s^{-1})	0.2857	0.7143	0

Vorticity and sediment conc. spatial scales **distant kinematic cousins**!
We expect a strict **inverse** proportionality.

Physical Interpretation of Emission Matrix 3
Vorticity and Sediment Concentration Spatial Scales

- Low vorticity levels -> small (50%) and **large** sediment spatial scales (40%)

  Q: Why?

  A: Low vorticity (low shear) allows for **large scale sediment amalgamation** and **small scale residuals**

Low Vorticity 13.0 – 14.5 (s^{-1})	Small Scale 0.5	Med. Scale 0.1000	Large Scale 0.4000

- Medium vorticity levels -> **small, medium, and large spatial scales** supported (~30% for all)

- Q: Why?
- A: Fluid vorticity and stress levels increase -> large spatial scales **break downs into all scales**

Physical Interpretation of Emission Matrix 3

Vorticity and Sediment Concentration Spatial Scales

- High vorticity levels -> 71% **medium** spatial scales
  -> 0% **large** spatial scales

High Vorticity 16.0 – 17.5 (s^{-1})	Small scale	Med. Scale	Large Scale
	0.2857	0.7143	0

- Q: Why?
- A: High vorticity levels -> high shear -> **destroys** large spatial scales

- **Low Vorticity –> small and large spatial scales**
- **High Vorticity –> medium and small spatial scales**

a) Weak enough to **support** large spatial scales
b) Strong enough to **destroy** large spatial scales

- Applicable **geo-intelligence systems describing adversarial behavior**
- E.g. Human systems feel 'stress' (cause) and coagulate and disperse (effect) in complex ways!

Knowledge Gradient Policy Information Ranking

Consider the problem:

1) 9 measurement (7 surface and 2 sub-surface) array

2) Leadership **projects future values** for 9 variable state

3) Leadership has **limited amount of resources** to take data

Q: What **order** should the variables be sampled over time to reach the projected goal state?

Question of **HOW** to collect information efficiently.

A: Knowledge gradient policy (KGP) processing = optimal learning

Knowledge Gradient Policy Information Ranking

- Estimate **path** towards the mean goal state S^* $(\theta^*, \sum^*)$

  1) Assume a prior mean vector θ^0 and covariance matrix $\sum^0$
     Mean goal state vector = [# # # # # # # # #]

  2) S^n $(\theta^n, \sum^n)$ = Bayesian belief state at **time n**

  3) **Learn or approach** goal state by

     a) **sampling** the data mean turbulent feature values (information sources)

     and

     b) **choosing** 1 variable out of the 9 at every n

- The criterion or policy used in choosing = **knowledge gradient policy**

Knowledge Gradient Policy Information Ranking

- Knowledge gradient =

  i) amount by which the state improves if feature $x' = x_M$ from M=9 array is selected

  ii) **marginal value** of a measurement in terms of **information value** gained

- **Information value** measured via utility function $X^{\pi,n}(S)$

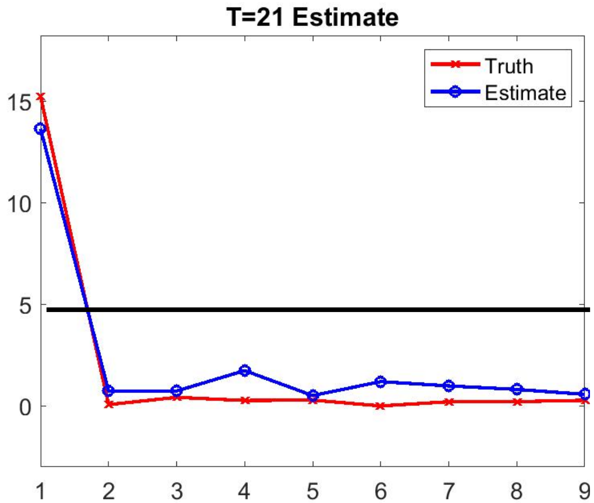
- Optimal decision choice = choice that causes largest **change** in $X^{\pi,n}(S)$
  -> maximizes **expected reward**
  -> minimizes opportunity cost

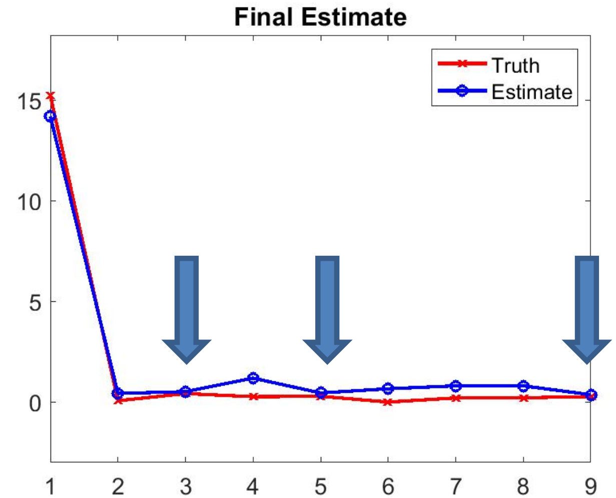
- Updated Bayesian state produces an **optimal state path through time**

~ **Method of steepest descent** $\mathbf{x}_{k+1} = \mathbf{x}_k - t_k \nabla f(\mathbf{x}_k), \quad k = 0, 1, 2, \ldots,$

Knowledge Gradient Policy Information Ranking

Prior = 5





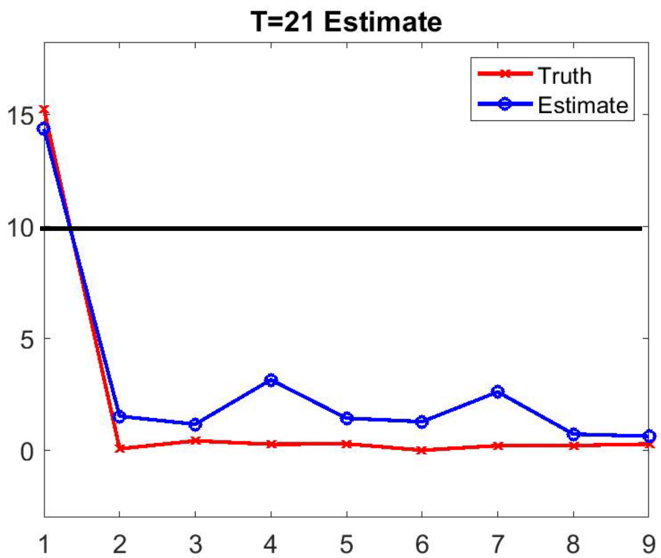
Truth = red
Estimate = blue

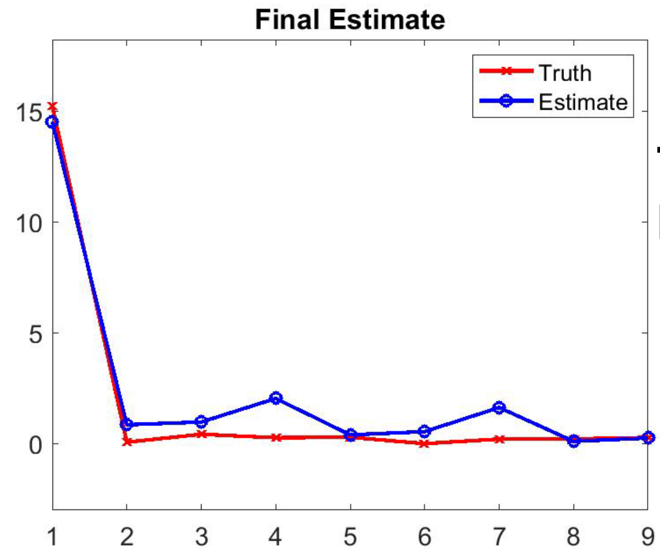
Var 1 = true mean value **Var 2-9 = 2 X true mean value**

- T = 21 estimate **less accurate** than T = 41 estimate
- KGP algorithm needs time to approach to truth
- Surface variable 3, 5, and 9 **converge first** (cross flow spatial scales, RMS w velocity, ICA based concentration spatial scales)
- **Some variables may be more significant in Bayesian goal state march!**

Knowledge Gradient Policy Information Ranking

Prior=10



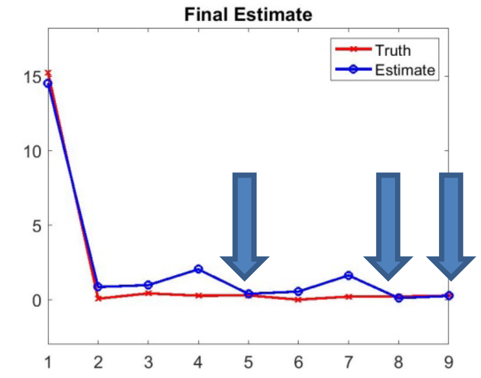


Truth = red
Estimate = blue

- Both estimates are overall **less accurate** than previous Prior = 5 case
- Vorticity is estimated very well compared to the Prior = 5 case
- **Lack of overall variable convergence** suggests that **Prior = 10 is too high** and more convergence time is needed

Knowledge Gradient Policy Information Ranking

- RMS surface w **velocity (5)**
- PCA-based surface **w velocity scales (8)**
- ICA-based surface **concentration scales (9)**



converge first !

Different set of variables to consider when seeking to attain goal state (because prior =10)

<u>Overall KGP Conclusions:</u>

- Goal state convergence time T **varies** depending on:
  1) variable correlation **(covariance)** 2) **priors assumed**.

- **What we believe affects how we obtain goals!**

Conclusions

- **Bayesian algorithms** applied to DPF data can be used to rationally understand simulated turbulent shear flow structure

1) **HMM models** captures the dynamic, sediment-induced **nonlinear flow dampening** in a sparsely sampled fluid flow.

2) **KGP algorithm** provides rational, resource saving guidance as to **how** to attain a goal state based on **Bayesian learning** 'powered' by information source covariance.

- **Not just data interpolation** but a crude way to inject a rudimentary sense of 'mind' using a functional policy for data paucity problems

- Developed algorithms possibly applicable to crowd turbulence

- **Presently seeking ways to utilize BNN software to automate and ease calculations.**