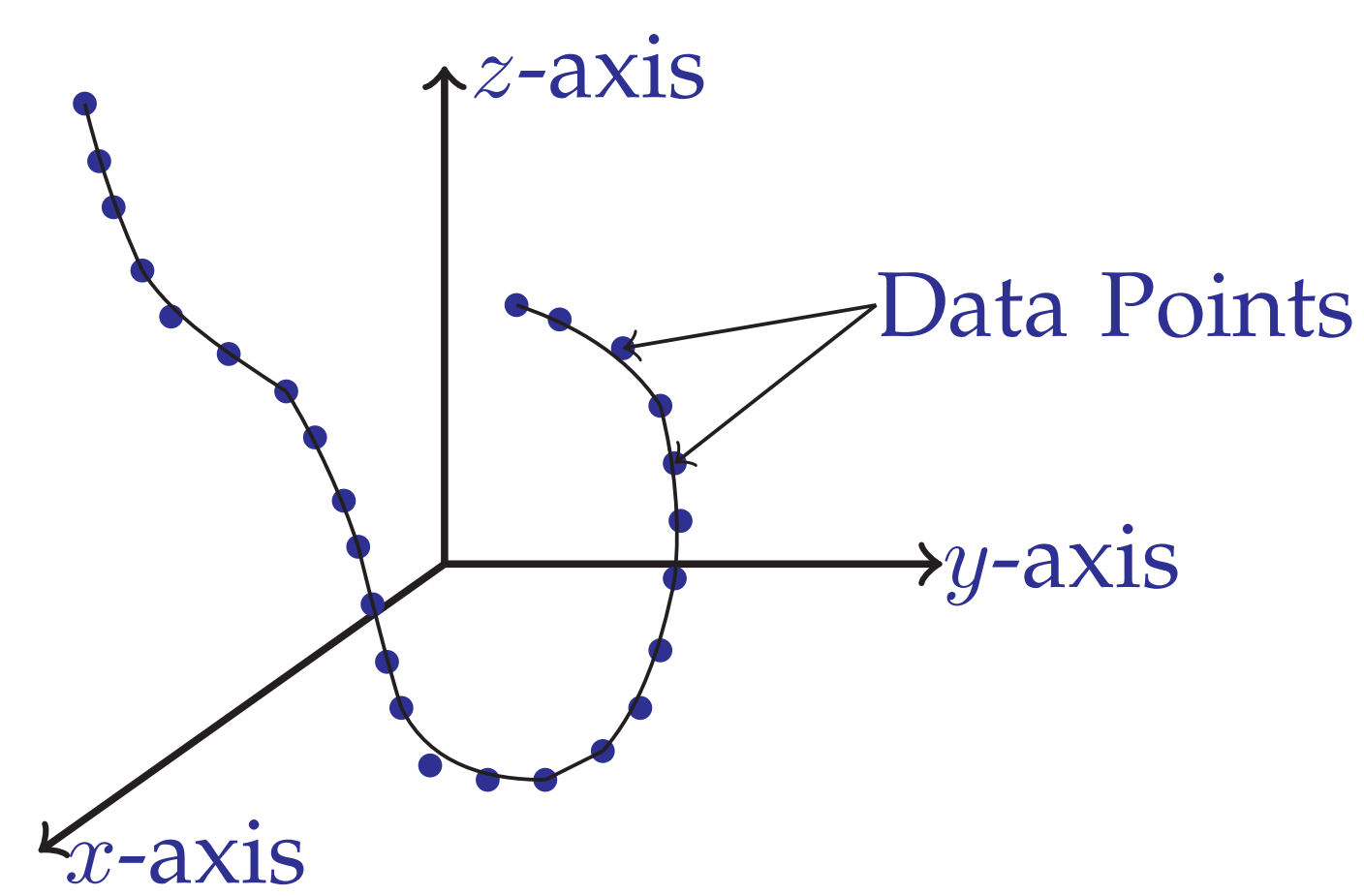


PROBLEM

Given a time series of observed positions $\{r_i\}_{i=0}^N$ in three dimensional space, our primary objective is to generate a smooth trajectory to **fit these data points**.

- A **penalty term** is introduced to assure smoothness of the reconstructed trajectory.

$$\text{Fit Error} = \sum_{i=0}^N \|r(t_i) - r_i\|^2 + \lambda \int_{t_0}^{t_N} (\text{Suitable Path Cost}) dt$$



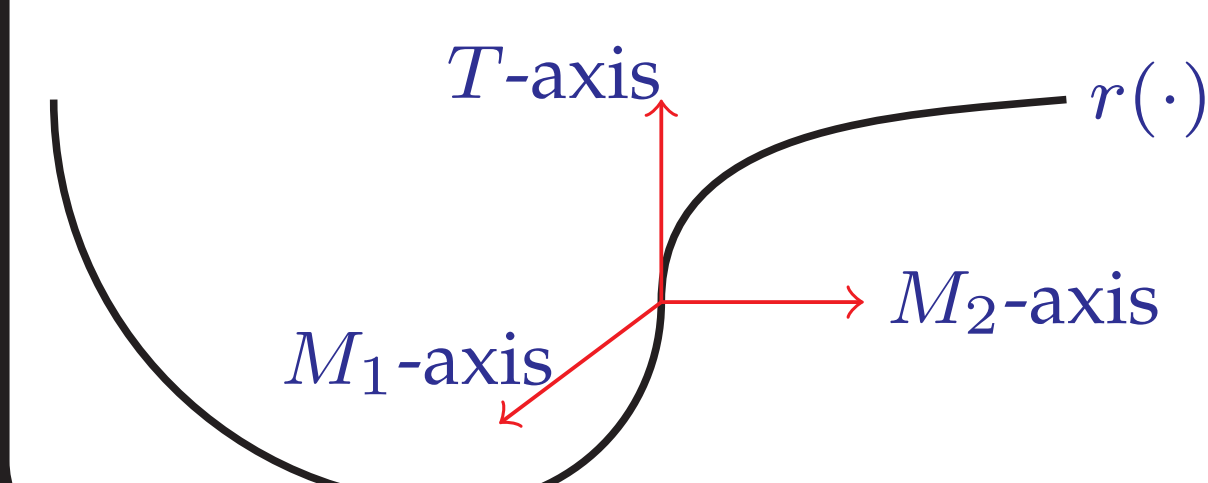
- **BUT** the relative importance of the fit error with respect to the penalty term is not known *a priori*.
- The optimal value of the regularization parameter (λ) is chosen using **ordinary cross validation**, and the optimal value depends on the **signal-to-noise ratio in the data**.

GENERATIVE MODEL I

$$\begin{aligned} \dot{r} &= \nu T \\ \dot{T} &= \nu (k_1 M_1 + k_2 M_2) \\ \dot{M}_1 &= -\nu k_1 T \\ \dot{M}_2 &= -\nu k_2 T \end{aligned} \quad (1)$$

- **Penalty Term** to ensure smoothness:

$$\int_{t_0}^{t_N} (k_1^2 + k_2^2 + \dot{\nu}^2) dt$$



GENERATIVE MODEL II

$$\begin{aligned} \dot{r} &= v \\ \dot{v} &= a \\ \dot{a} &= u \end{aligned} \quad (2)$$

- **Penalty Term** to ensure smoothness:

$$\int_{t_0}^{t_N} (u^T u) dt$$

MODEL II → MODEL I

$$\begin{aligned} \nu &= \|v\| \\ T &= \frac{v}{\|v\|} \\ \dot{T} &= \frac{1}{\nu} (a - (a \cdot T)T) \\ \kappa &= \frac{\|\dot{T}\|}{\nu} \\ \tau &= \frac{v \cdot (a \times u)}{\|v \times a\|^2} \end{aligned}$$

MODEL I → MODEL II

$$\begin{aligned} v &= \nu T \\ a &= \dot{\nu} T + \nu^2 k_1 M_1 + \nu^2 k_2 M_2 \\ u &= (\ddot{\nu} - \nu^3 (k_1^2 + k_2^2)) T \\ &\quad + (3\nu \dot{\nu} k_1 + \nu^2 \dot{k}_1) M_1 \\ &\quad + (3\nu \dot{\nu} k_2 + \nu^2 \dot{k}_2) M_2 \end{aligned}$$

RECONSTRUCTION THROUGH ERROR MINIMIZATION

Model I (Nonlinear)

- Approximation by **piecewise constant** speed and curvature, transforms the problem into a **non-convex numerical optimization problem** [2].
- MATLAB routine: **fminunc**.
- The algorithm is capable of estimating curvature with higher resolution, but the process is **time consuming**.

Model II (Linear)

- **Path-independence lemmas** and **Riccatti equation** ensure **global optimality of the solution** and **the solution is semi-analytic** [1].
- Reconstructed positions can be expressed as **linear combinations of raw data**, but the **linear weights vary across data points**.
- This method is **orders of magnitude faster** than the nonlinear version of the story.

WORK IN PROGRESS

- We are working with generative model I to reconstruct trajectories in a semi-analytic way.

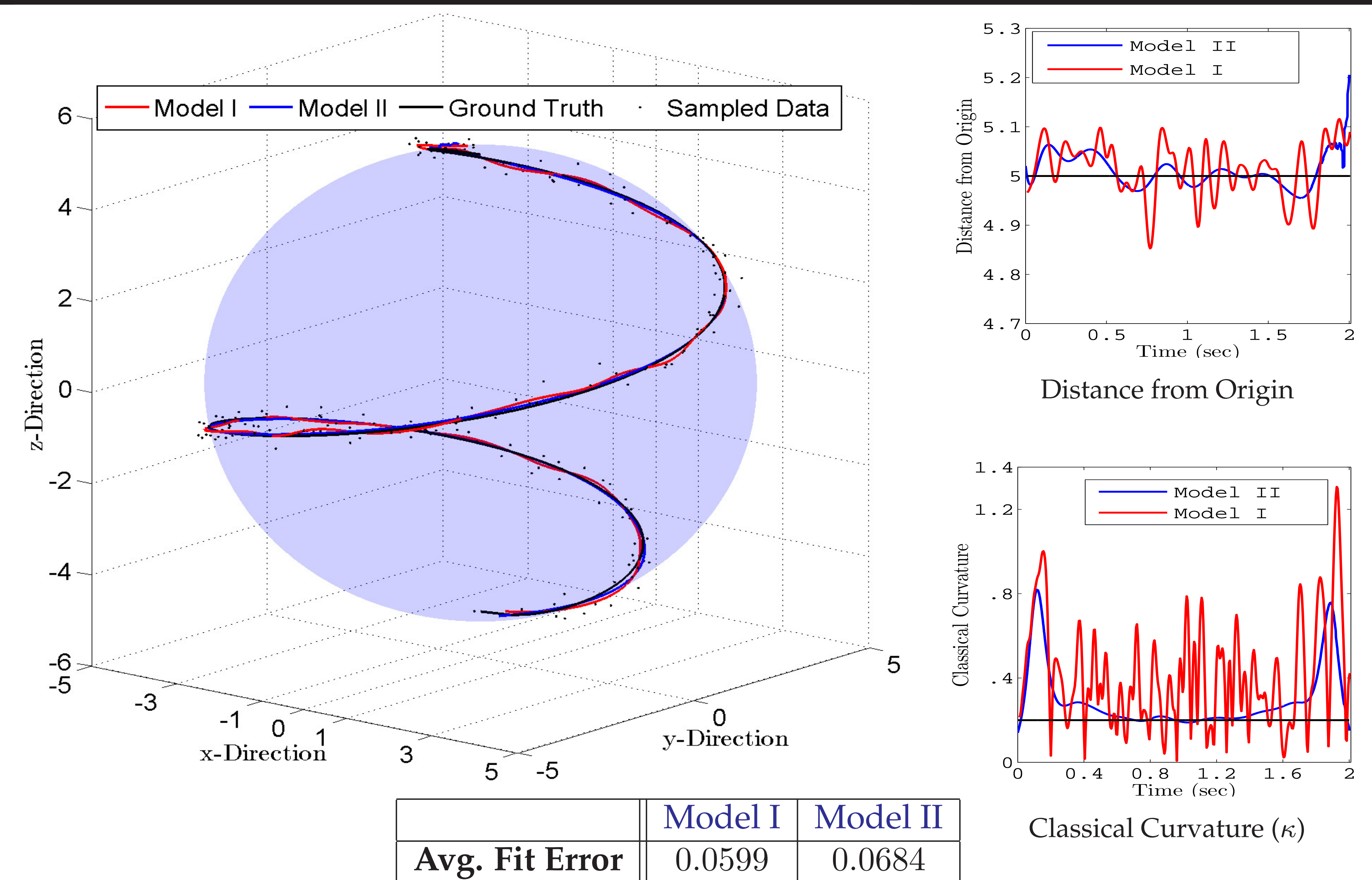
SOURCE CODE

The source code and compiled executables with an interactive interface are available at <http://www.isr.umd.edu/Labs/ISL/SMOOTHING/>

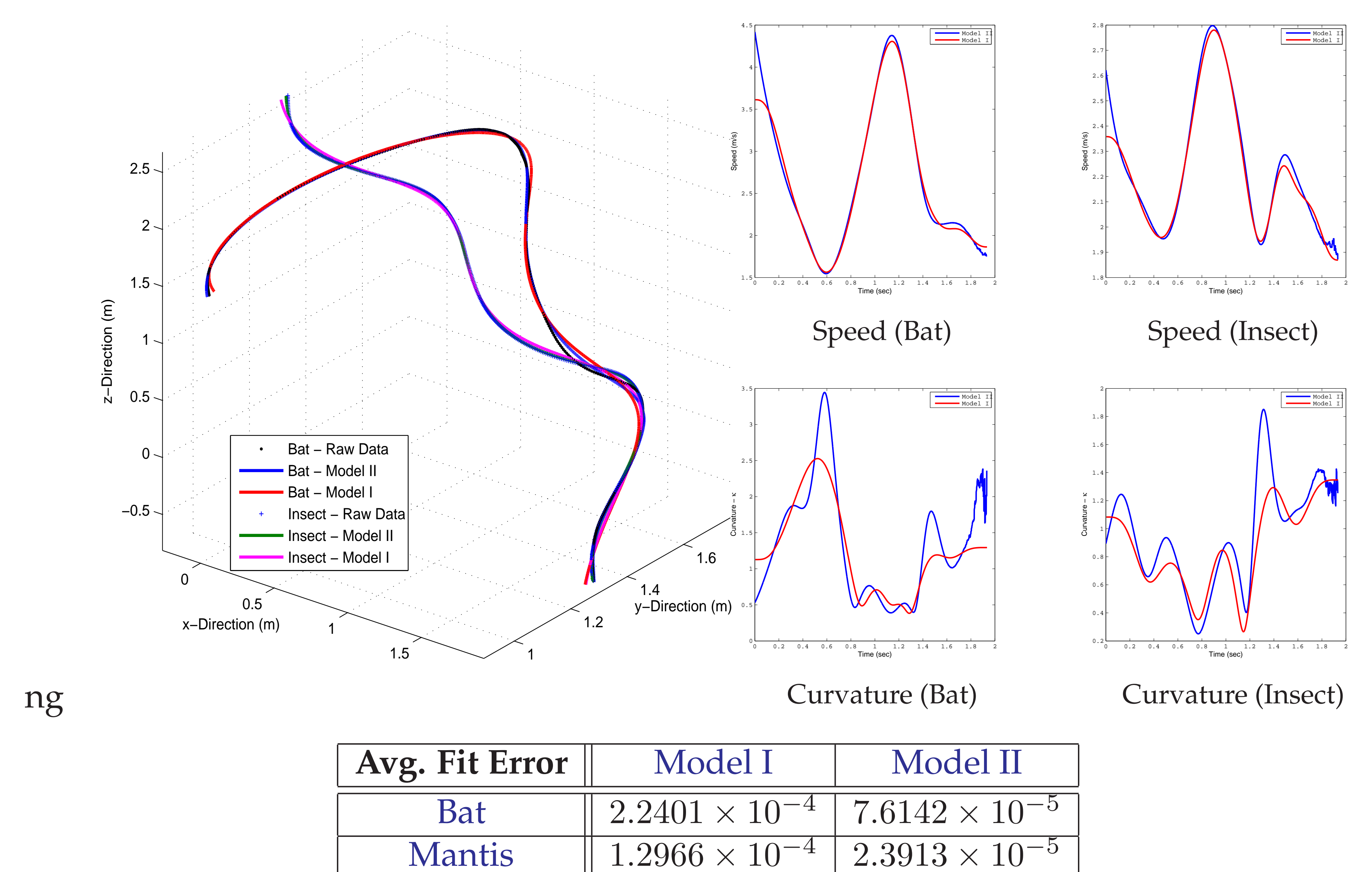
CHOOSING A REGULARIZATION PARAMETER (OCV)

- We use a subset of the given dataset to obtain a parameter estimate and use the rest of the data for performance validation under that particular value of the estimate.
- Here we use **leaving-out-one** strategy.
- Each data point is left out in turn and an estimate for the curve is derived from the rest of the data. The prediction error is computed at the left out data point and they are summed to yield the ordinary cross validation cost. An **optimal λ** minimizes the **total prediction error** (sampled variance).

RESULTS (SYNTHETIC DATA - CURVE ON A SPHERE)



RESULTS (BAT-MANTIS PURSUIT EVENT)



REFERENCES

- [1] B. Dey, P. S. Krishnaprasad. *Trajectory Smoothing as a Linear Optimal Control Problem*. in Proceedings of Allerton Conference on Communication, Control, and Computing, 2012.
- [2] P.V. Reddy. *Steering Laws for Pursuit*. Masters' Thesis, University of Maryland, 2007.

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