

Coupled Oscillator Model parameter optimization with UKF on fMRI data

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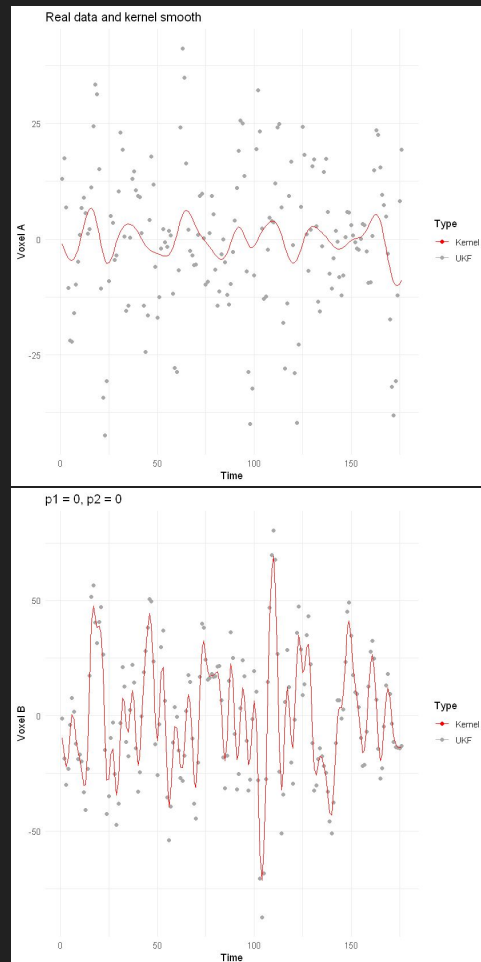
Goals of the Project

This project aims to leverage nonlinear system identification techniques, focusing on the **Unscented Kalman Filter (UKF)**, to enhance modeling and understanding of neural dynamics from **fMRI** data, addressing the direct challenges of noise and indirect measurement.

- ✓ UKF on different fMRI signals (different regions, different subjects)
- ✓ Coupled oscillator model modification - New model
- ✓ Parameter estimation methods comparison - Optimization methods
 - Measuring coupling on more than 2 regions simultaneously - Possible

Datasets

- Voxel A & B data (accessible through Harvey)
- Harvard - Oxford atlas dataset
 - 2 subjects
 - 1 ASD and 1 Normal condition
 - voxel A: 18th voxel (Left Amygdala)
 - voxel B: 26th voxel (Left Accumbens)
 - <https://scalablebrainatlas.incf.org/human/HOA06>
 - <https://www.kaggle.com/datasets/mhkoosheshi/asdfmri?resource=download&select=Harvard-Oxford+Atlas+%28Label+of+Brain+Regions%29.csv>



Normal Subject 01 voxels #18 and #26

Coupled Oscillator Model

Coupled pendulum approximation. “**p**” are unknown parameters to estimate (other parameters could also be optimized or determined).

$$w1 + a1 \sin\theta1 + p1 \sin\theta2,$$

$$w2 + p2 \sin\theta1 + a4 \sin\theta2.$$

** In the experiment, $w1$ & $w2 = 0$, $a1$ & $a4 = 1$.*

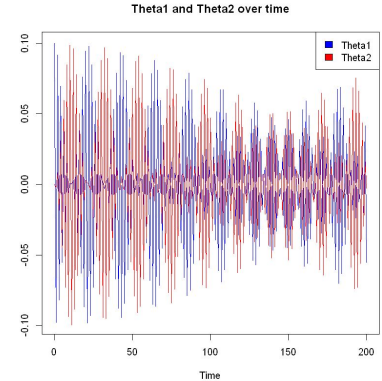
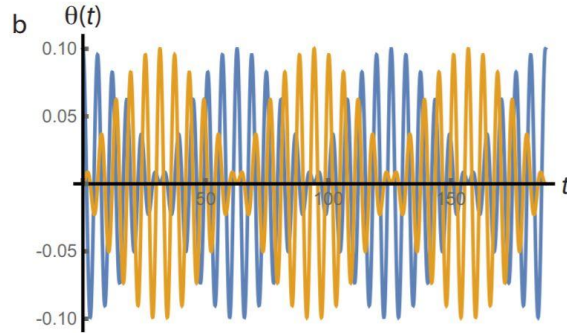
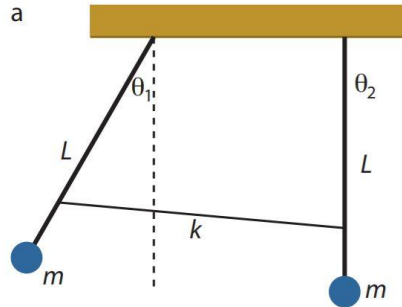
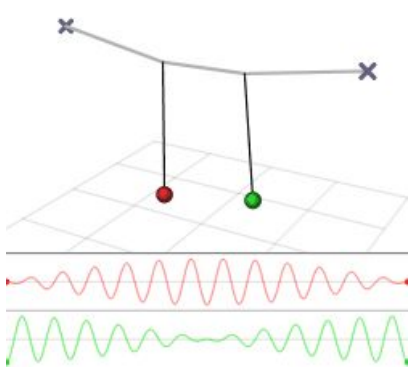
New!

Coupled Oscillator Model

Two identical pendulums of length L and mass m , which are connected by a weak spring with spring constant k .

$$L \ddot{\theta}_1 = -g \sin \theta_1 - k L (\sin \theta_1 - \sin \theta_2),$$

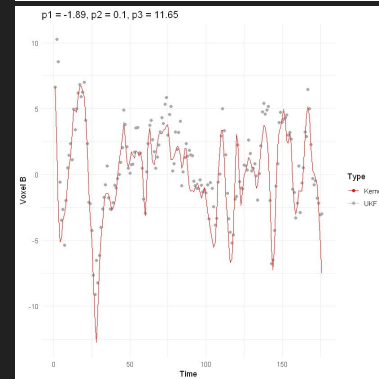
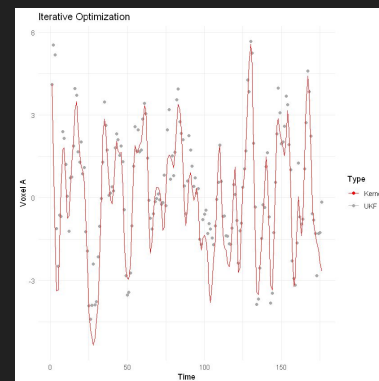
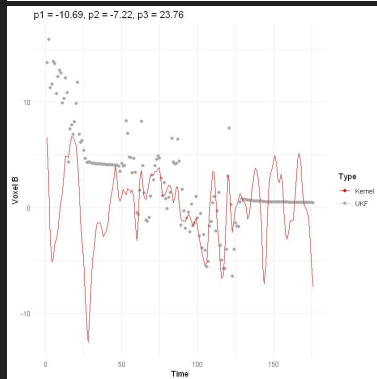
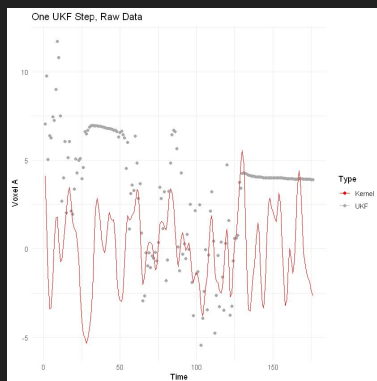
$$L \ddot{\theta}_2 = -g \sin \theta_2 + k L (\sin \theta_1 - \sin \theta_2)$$



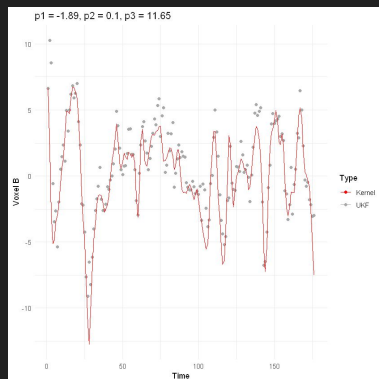
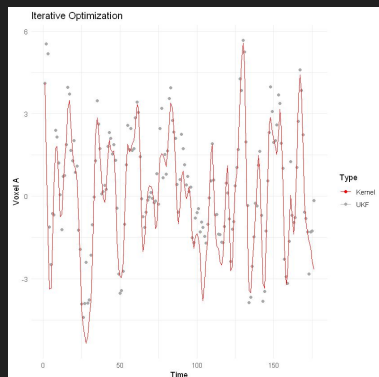
UKF & New Coupled Oscillator Model

One Pass, $g = -10.69$, $L = -7.22$, $k = 23.76$, $\chi^2 = 62.6$

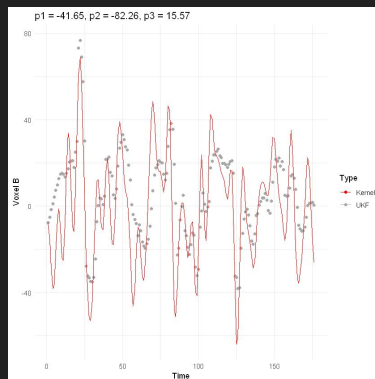
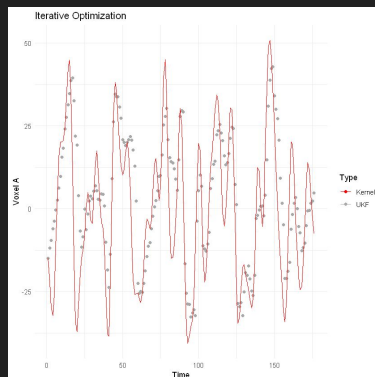
Iterative Opt., $g = -1.89$, $L = 0.1$, $k = 11.64$, $\chi^2 = 4.33$



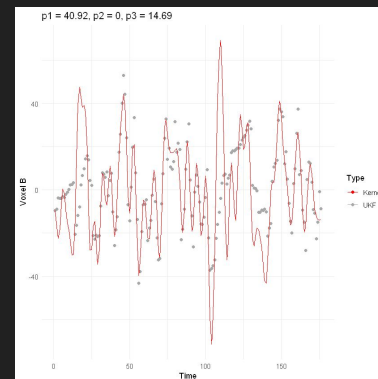
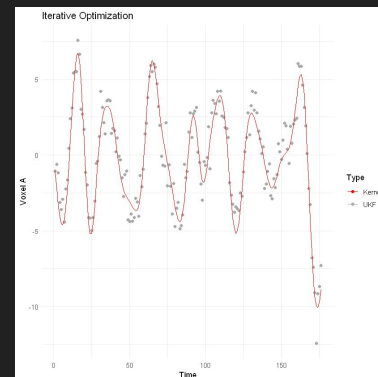
Iterative Opt. smoothed data, g
 $= -1.89$, $L = 0.1$, $k = 11.64$, $\chi^2 =$
 4.33



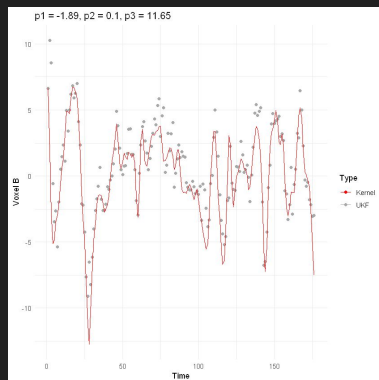
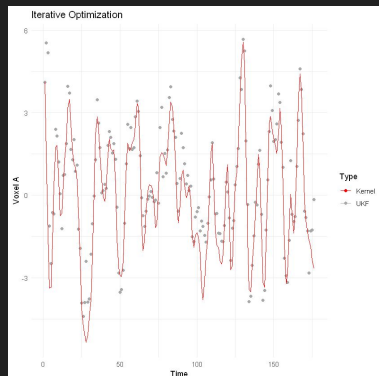
Iterative Opt. smoothed subj1
 (ADS Subject 01), $g = -41.65$, L
 $= -82.26$, $k = 15.57$, $\chi^2 = 592.5$



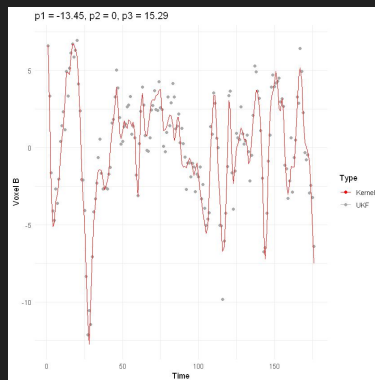
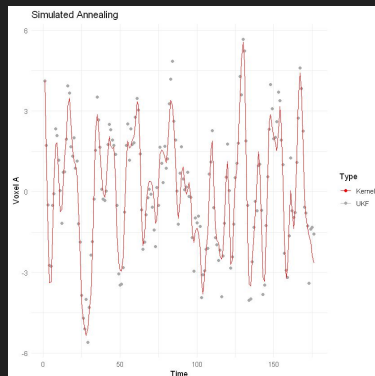
Iterative Opt. smoothed subj2
 (Normal Subject 01), $g = 40.92$,
 $L = -0.01$, $k = 14.69$, $\chi^2 = 315.4$



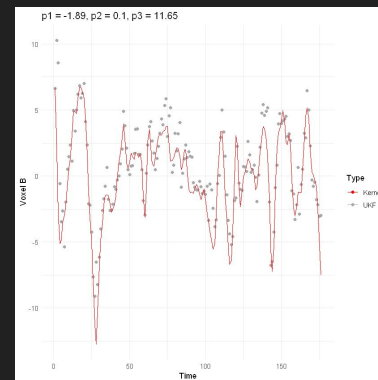
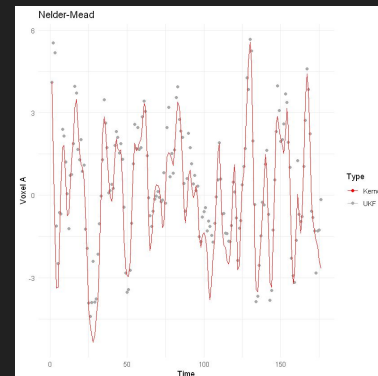
Iterative Opt. smoothed data, $g = -1.89$, $L = 0.1$, $k = 11.64$, $\chi^2 = 4.33$



Simulated Annealing smoothed data + UKF, $g = -15.4$, $L = 1.35$, $k = 15.53$, $\chi^2 = 1.4$



Nelder-Mead smoothed data + UKF, $g = -1.89$, $L = 0.1$, $k = 11.64$, $\chi^2 = 4.33$



Conclusion

- New Coupled Oscillator model is efficient on fMRI data analysis
- As the number of parameters increase, the runtime and the search space increases.

Future Work

- More datasets and correlated voxels can be examined
- New model can be modified to have more parameters
- Parallelization for larger search spaces
- UKF function modifications

References

- [https://phys.libretexts.org/Bookshelves/University_Physics/Mechanics_and_Relativity_\(Idema\)/08%3A_Oscillations/8.04%3A_Coupled_Oscillators](https://phys.libretexts.org/Bookshelves/University_Physics/Mechanics_and_Relativity_(Idema)/08%3A_Oscillations/8.04%3A_Coupled_Oscillators)
- <https://scalablebrainatlas.incf.org/human/HOA06>
- <https://www.kaggle.com/datasets/mhkoosheshi/asdfmri?resource=download&select=Harvard-Oxford+Atlas+%28Label+of+Brain+Regions%29.csv>
- <https://groups.seas.harvard.edu/courses/cs281/papers/unscented.pdf>