Section:
Pattern identification and steering for spatio-temporal and network dynamics

Project Summary

- **Background**: Attractor clustering for pattern detection
  - DMDC
  - CkNN for attractor clustering
  - Application to Liquid Crystal data
  - Preliminary study of geometric pattern identification (dim/vol)
- **Observability**: Extension of DMDC to neuron data and spike trains
  - Introduce observability condition number for Takens embedding theorem
  - Empirical estimation of observability conditioning?
  - Improving conditioning through convolution/low-pass filtering?
- **Pattern identification**
  - Step 1: **Attractor Discrimination**: DMDC+CkNN reconstructs/separates attractors
  - Step 2: **Pattern Identification**: Separate attractors may represent similar *patterns*
    - *Topological*: Attractors with the same topology have a similar dynamical constraints at a very coarse level
    - *Geometric*: Attractors with the same geometry only differ in how the pattern evolves dynamically
    - *Dynamical*: Attractors with the same dynamical properties (Lyapunov spectrum and stochastic forcing) represent identical patterns
  - Step 3: **Steering**: Move to nearest attractor with desired pattern
    - Transition probabilities
    - Basin identification for pattern classes?
    - State space exploration?
- **Application to Spatiotemporal and Network Dynamics**
  - **Diffusion distance**: Hierarchical metric using a *dictionary* built from data subsets which are localized in the spatial or network structure. Can be designed to be invariant to spatial/network transformations (translation, rotation, ect.).
  - **Nematic Liquid Crystals**:
  - **Neuronal Networks**:

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1 Background and motivation

1.1 Preliminary research: Attractor clustering for pattern detection

References Cited