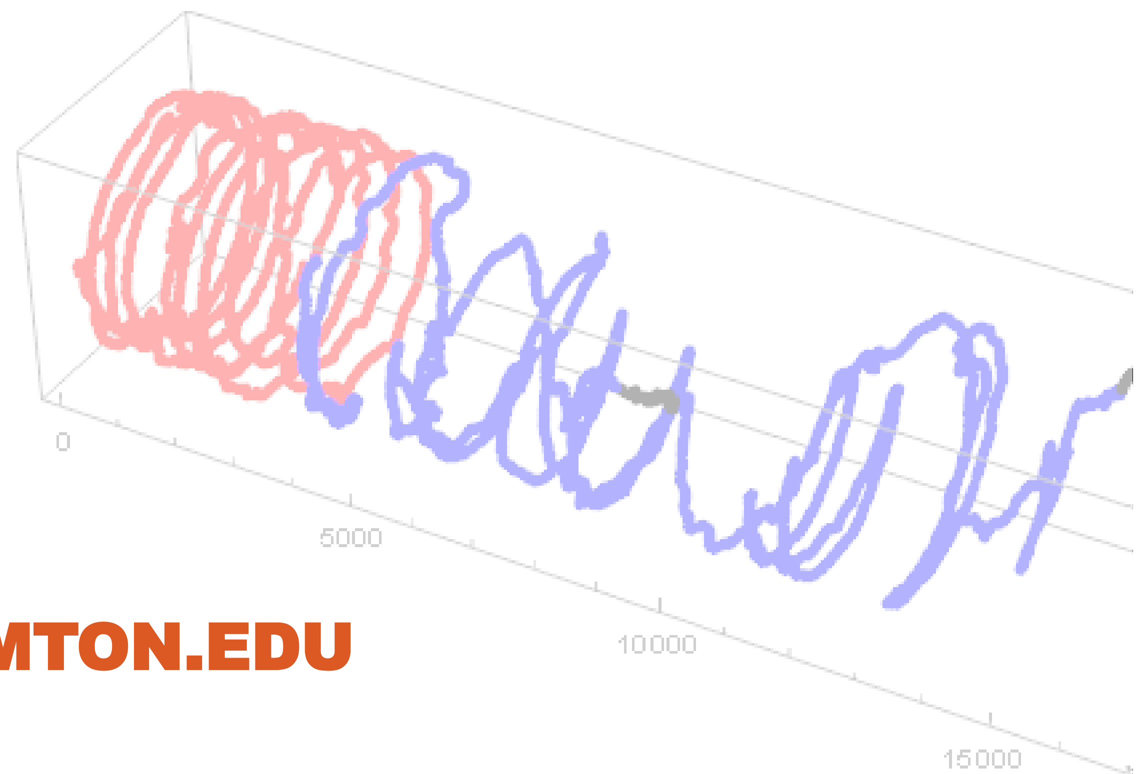
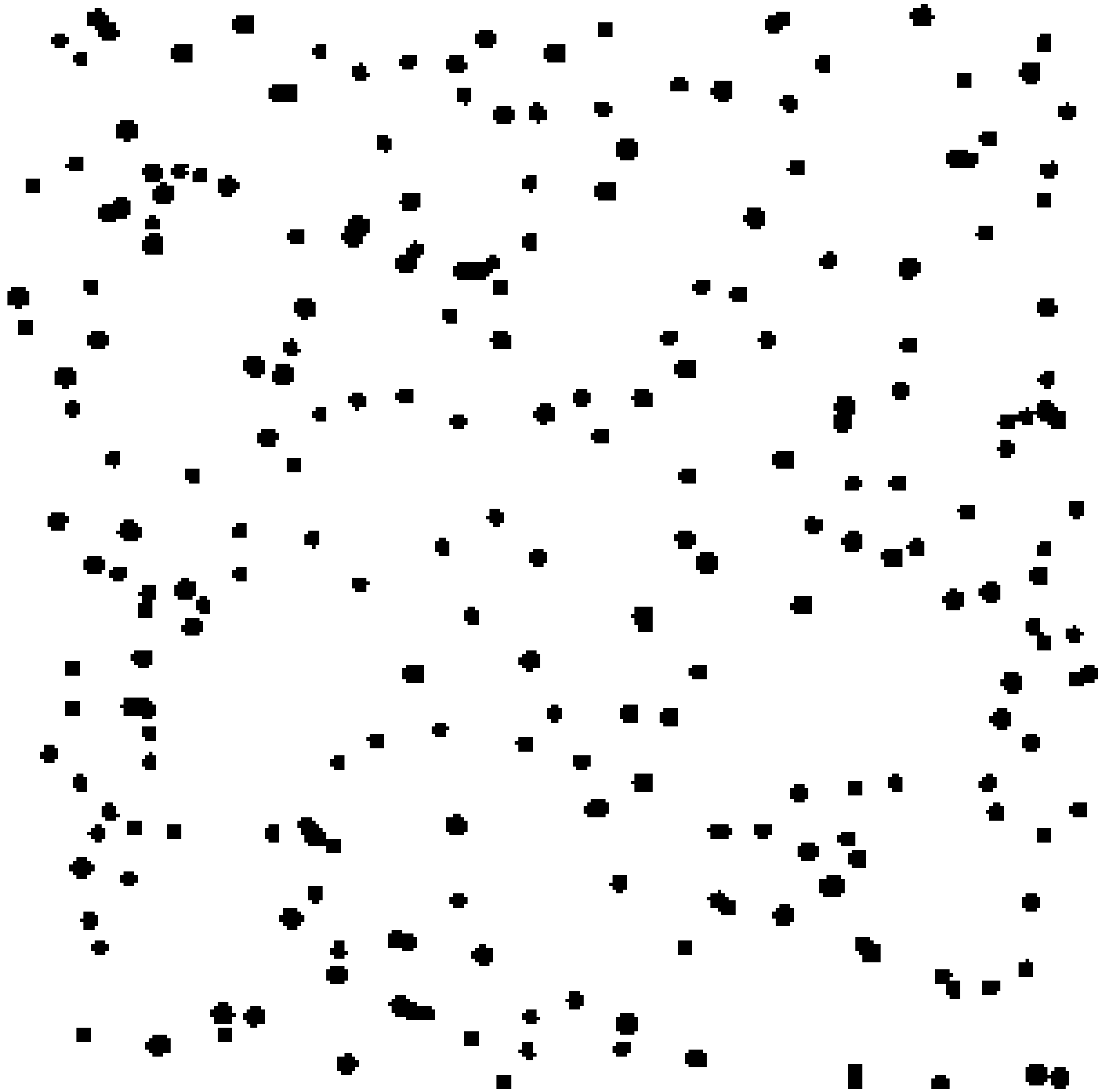
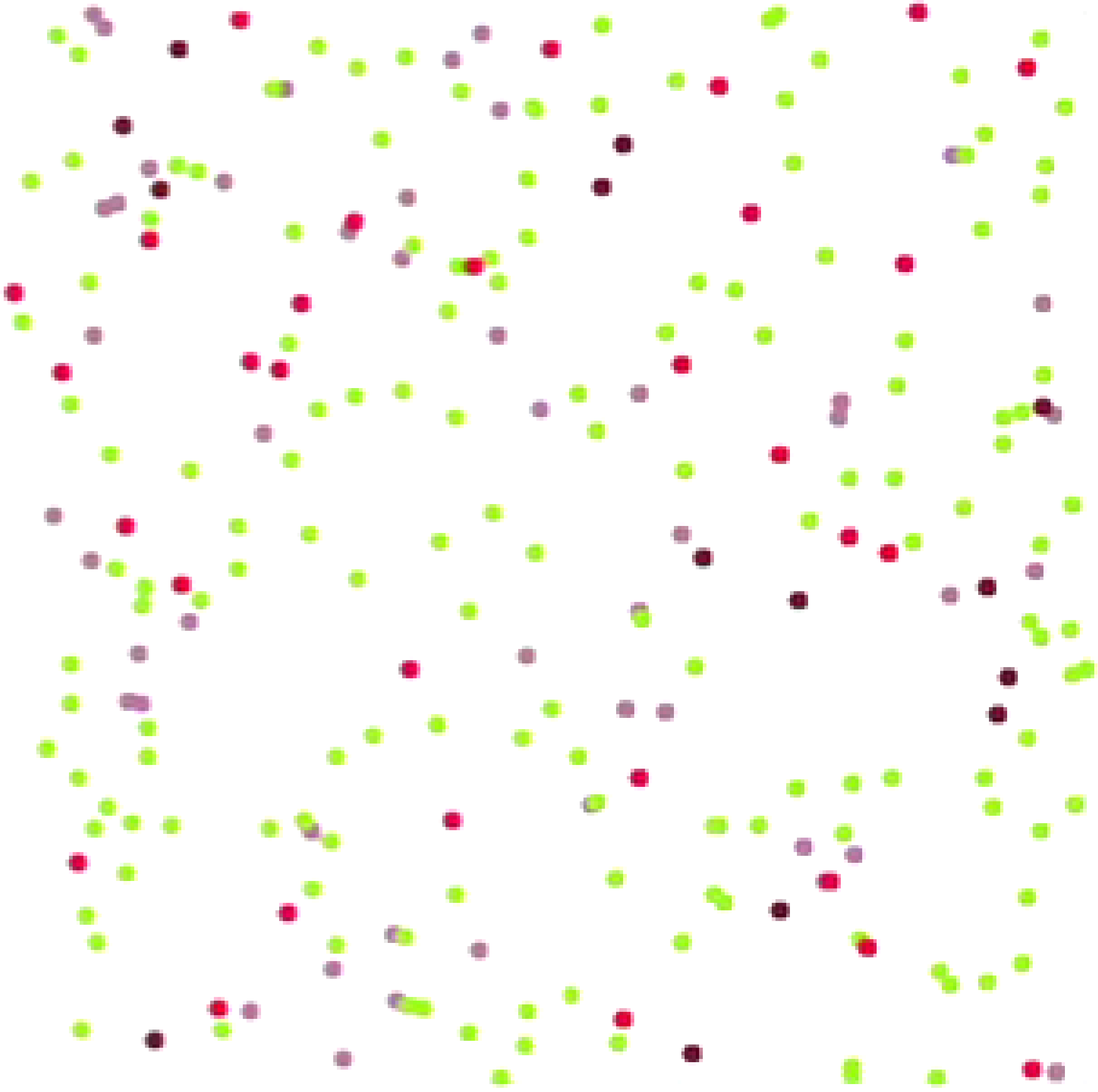
MODELING INDIVIDUAL BEHAVIORAL STATE TRANSITIONS FROM EXPERIMENTAL OBSERVATIONS OF TERMITE COLLECTIVES



HIROKI SAYAMA

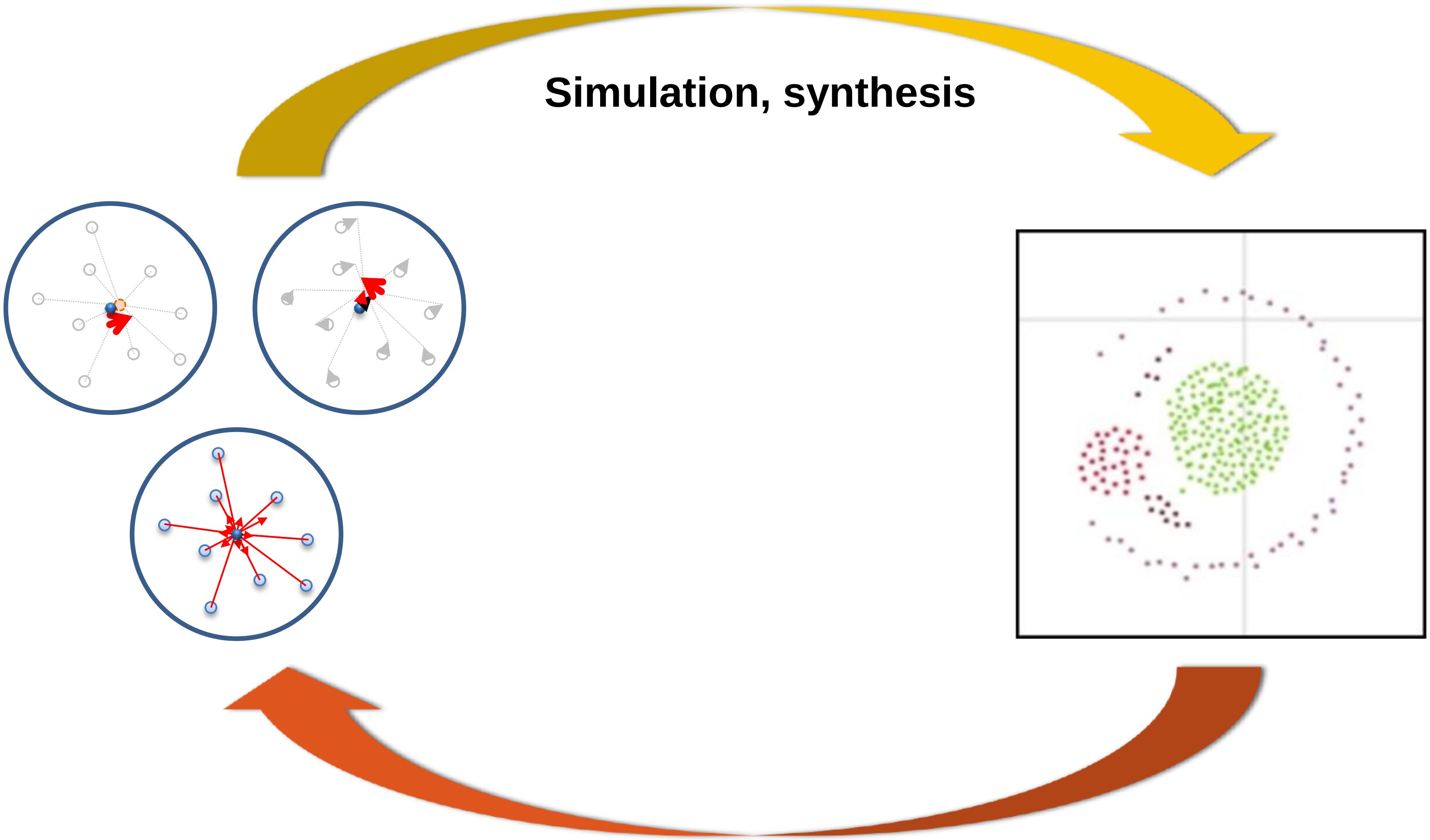
SAYAMA@BINGHMTON.EDU





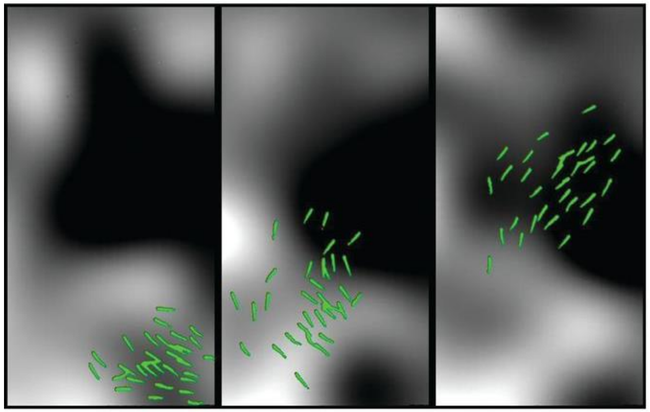
Sayama (2009) *Artificial Life* 15:105-114.

MOTIVATION

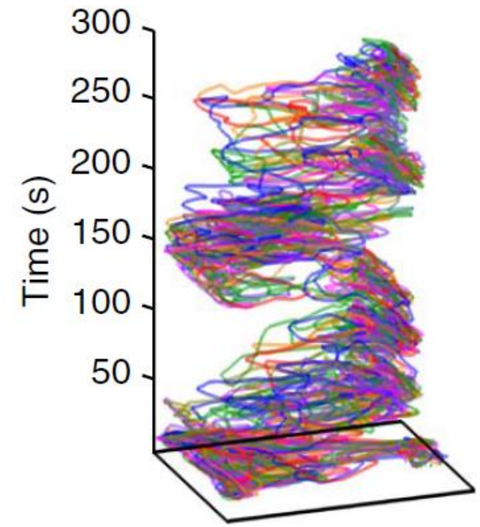


Inference of heterogeneous behavioral states/rules?

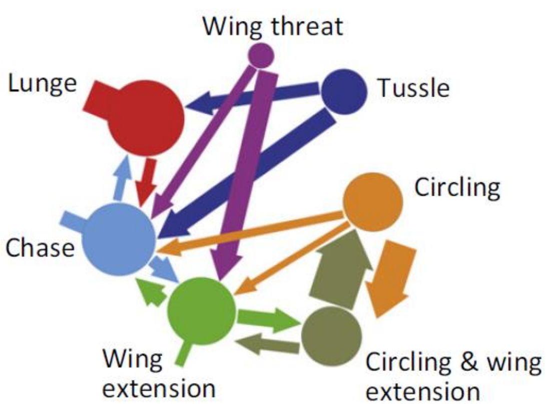
ANIMAL TRACKING, BEHAVIORAL CLASSIFICATION & MODELING



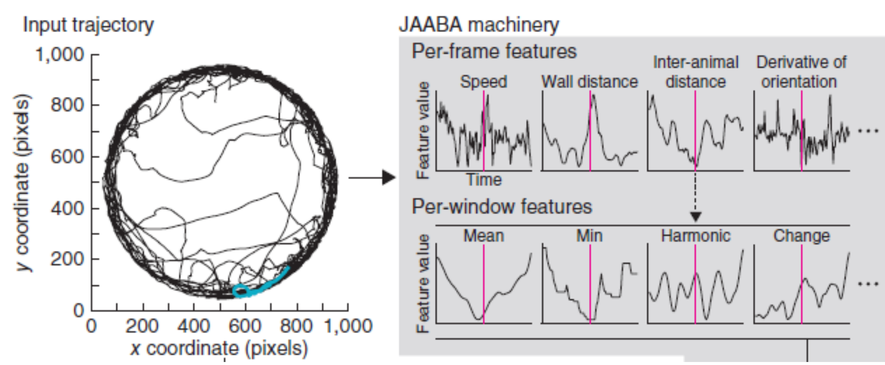
Berdahl et al. (2013)



Pérez-Escudero et al. (2014)



Dankert et al. (2009)



Kabra et al. (2013)

Comprehensive review by Dell et al. (2014)

TECHNICAL CHALLENGES TO BE ADDRESSED

Animal tracking:

Needs well-lit, controlled environment

Behavioral classification:

Needs manually entered behavioral labels

Behavioral modeling:

Little consideration of heterogeneity in collective

OUR APPROACHES

Animal tracking:

Use interactive robust semi-automated tracking

Behavioral classification:

Classify by using only physical properties of paths

Behavioral modeling:

Model behavioral heterogeneity in both time and space, and their interactions

PRELIMINARY TEST DATA

A low-resolution video recording of 26 termites freely moving in a Petri dish for 10 minutes

INTERACTIVE SEMI-AUTOMATED TRACKING

Works with low-res, not-so-bright videos too

Manual input of initial positions

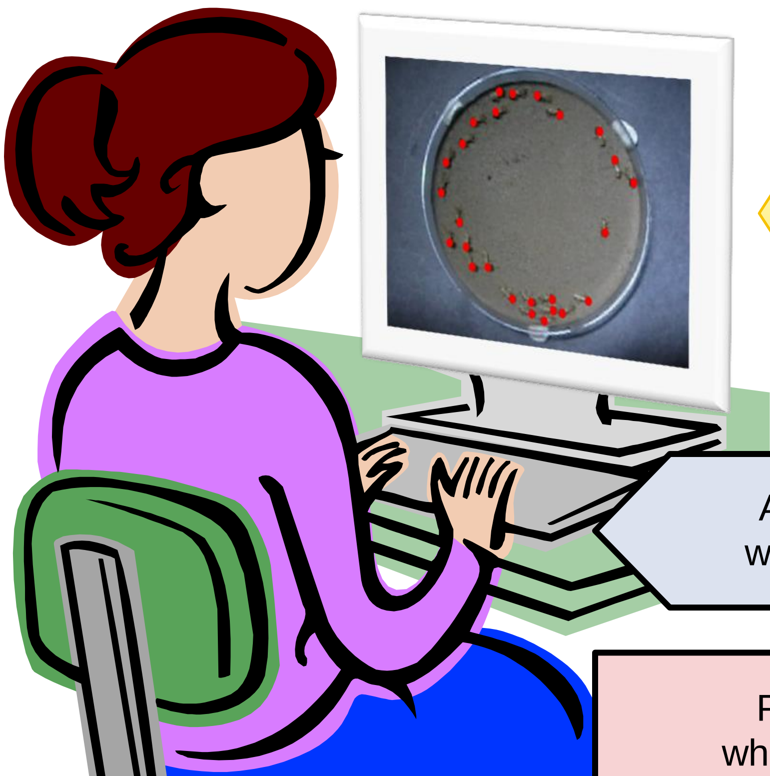


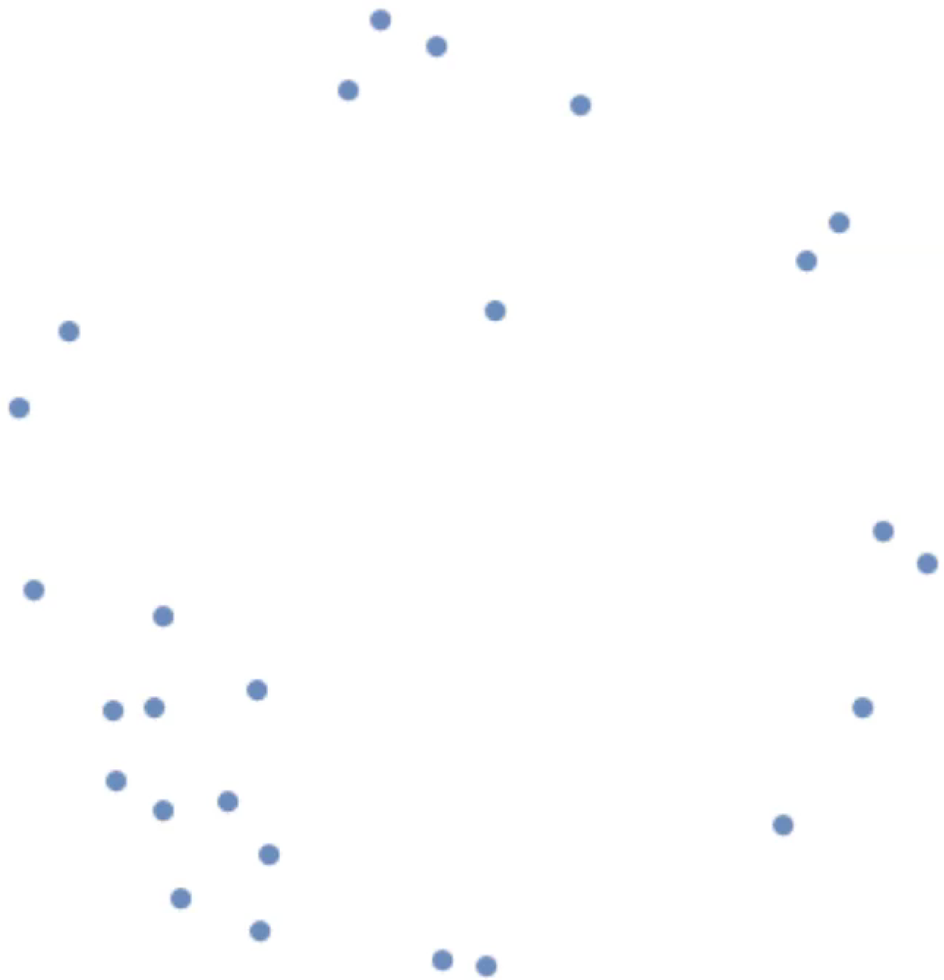
Image feature tracking by Wolfram Research Mathematica

(This does not require any biological/ecological information or well-lit environment)

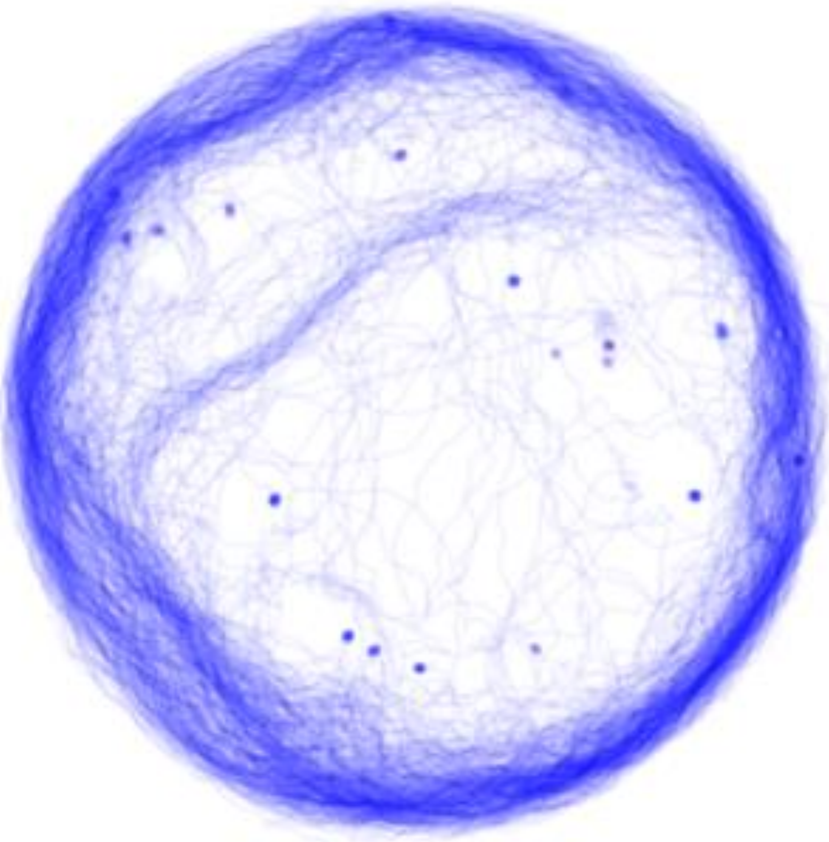
Asks for intervention when features are lost

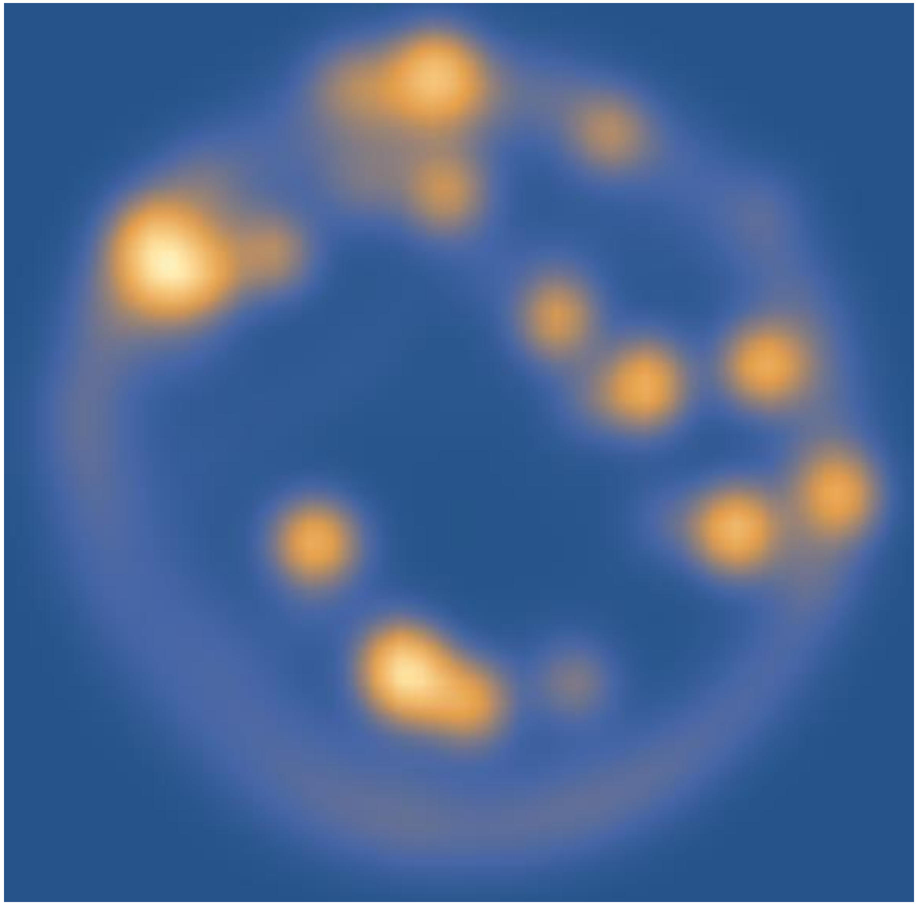
Pauses and corrects the positions when tracking points go off the targets

RESULTS

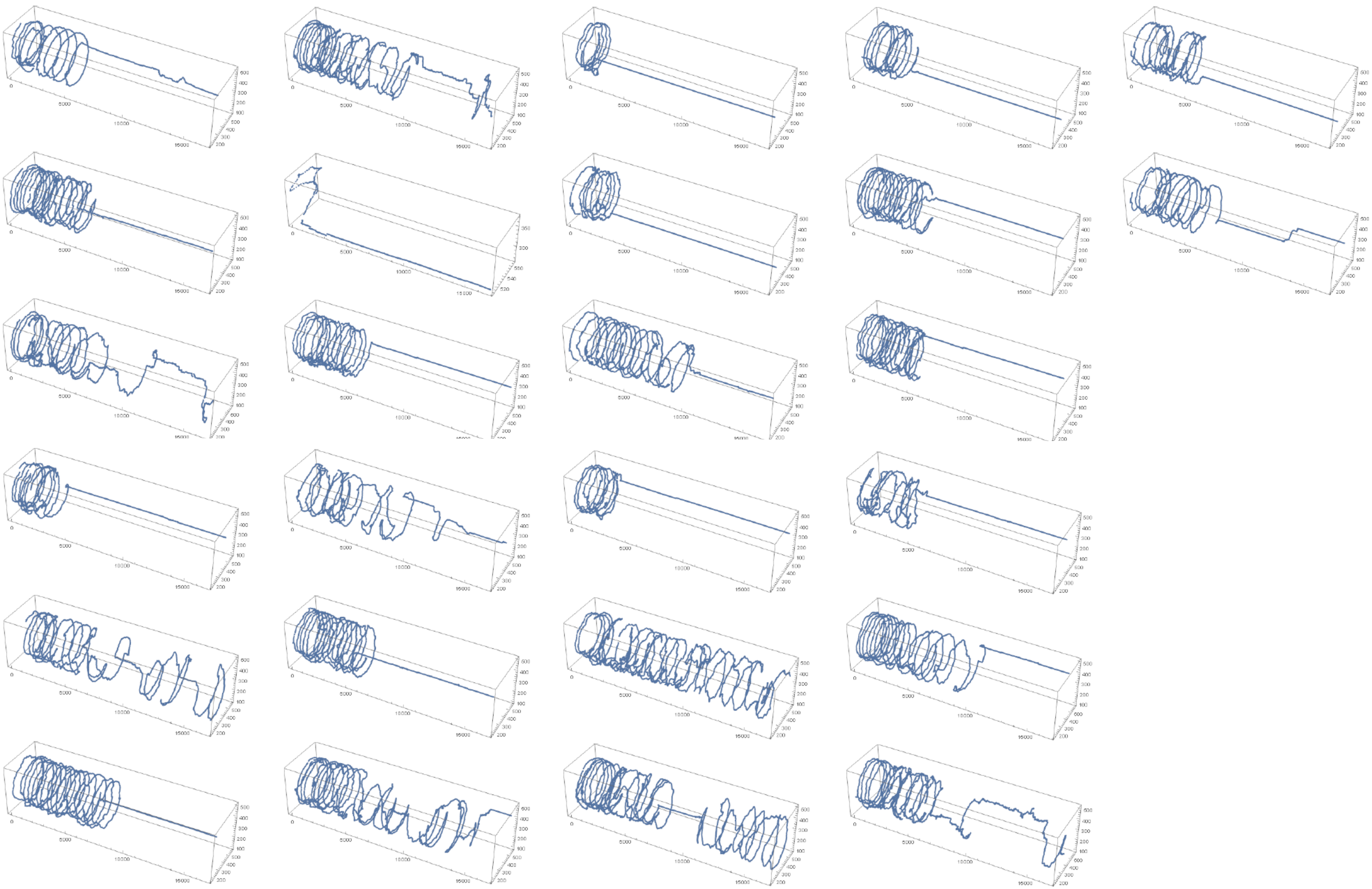


COLLECTIVE TRAJECTORIES

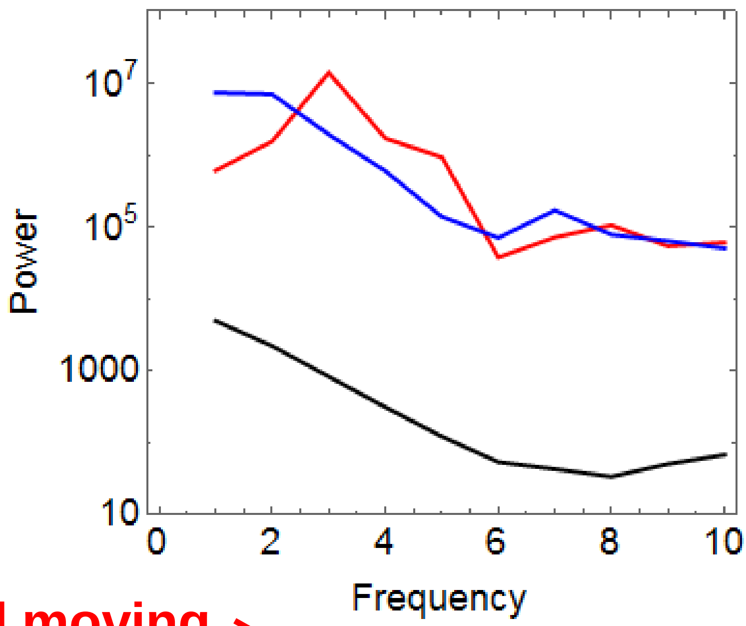




INDIVIDUAL TRAJECTORIES



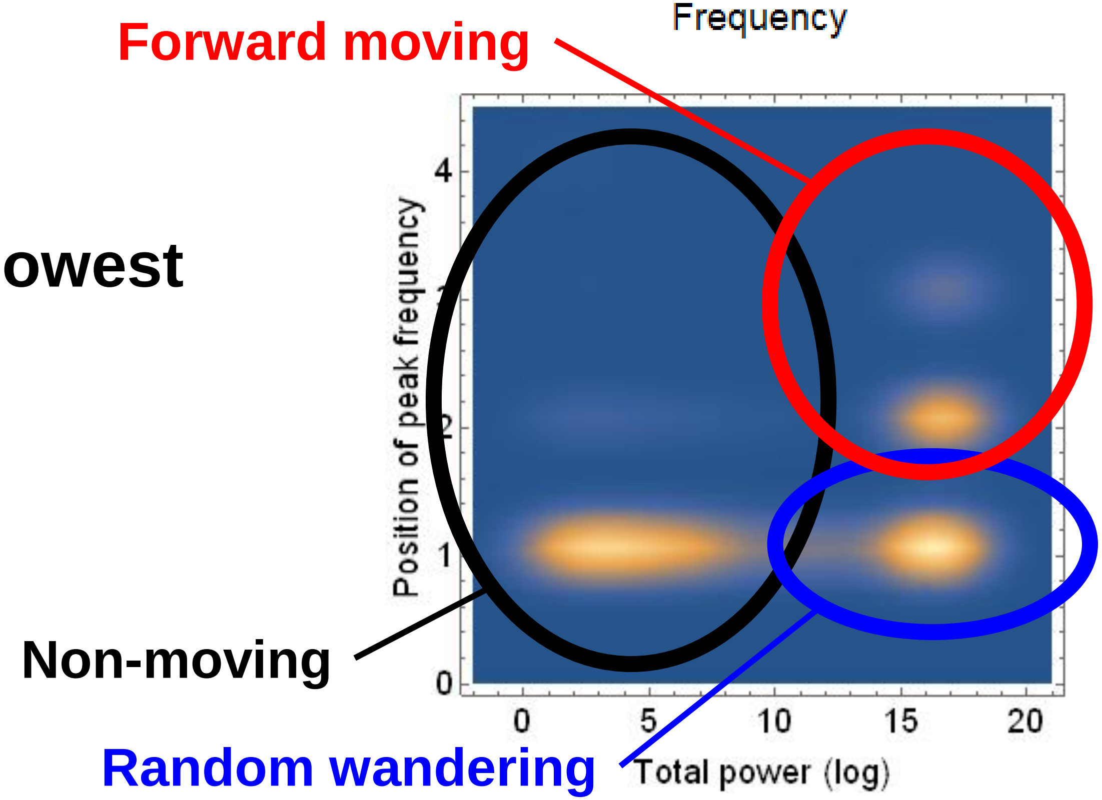
BEHAVIORAL CLASSIFICATION



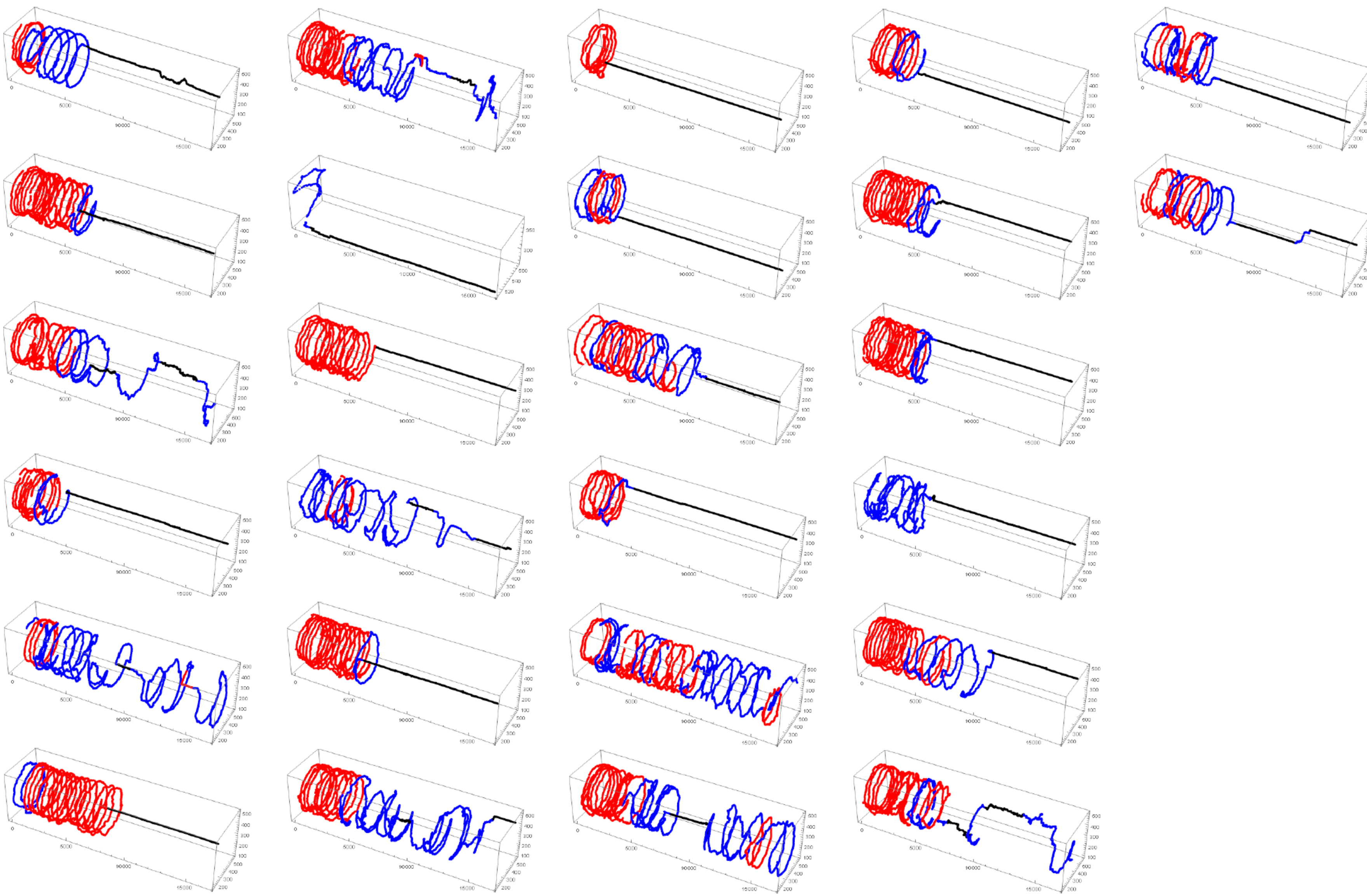
Used power spectra of short segments (1,000 frames ~ 30 sec.) of individual trajectories

Two metrics used

- Total power of ten lowest components
- Peak frequency



RESULTS



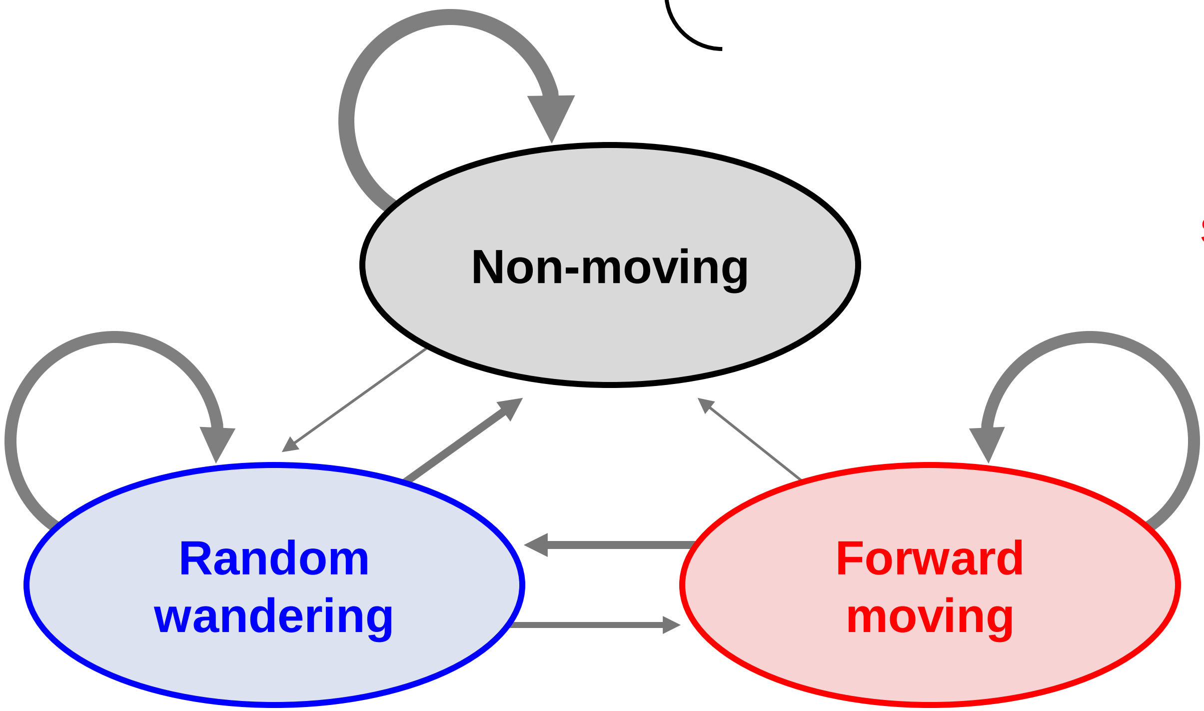
BEHAVIORAL MODELING (1) SIMPLE MARKOVIAN MODEL

Transition matrix:

$$\begin{pmatrix} 0.953 & 0.233 & 0.034 \\ 0.047 & 0.621 & 0.371 \\ 0. & 0.147 & 0.596 \end{pmatrix}$$

Dominant eigenvector:

$$\begin{pmatrix} 0.791 \\ 0.153 \\ 0.055 \end{pmatrix}$$



Cosine similarity = 0.993

Actual final states:

$$\begin{pmatrix} 20 \\ 6 \\ 0 \end{pmatrix}$$

BEHAVIORAL MODELING (2)
LOCAL INTERACTION MODEL

Counting # of other individuals nearby

Model (built for each behavioral state):

$$\boldsymbol{p} = \boldsymbol{t_s} + \boldsymbol{N_s}\,\boldsymbol{n}$$

Probability of next state
Independent transition prob.
Interaction matrix
\# of neighbors (per state)

$$\boxed{\begin{pmatrix} 0. \\ 0.02 \\ 0.98 \end{pmatrix}} = \begin{pmatrix} 0. \\ 0.03 \\ 0.97 \end{pmatrix} + \begin{pmatrix} 0.02 & 0. & 0. \\ 0.04 & -0.01 & -0.01 \\ -0.07 & 0. & 0.01 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

Given from data

$$= \boxed{\begin{pmatrix} 0. & 0.02 & 0. & 0. \\ 0.03 & 0.04 & -0.01 & -0.01 \\ 0.97 & -0.07 & 0. & 0.01 \end{pmatrix}} \boxed{\begin{pmatrix} 1 \\ 0 \\ 0 \\ 1 \end{pmatrix}}$$

Estimated

ESTIMATING INTERACTIONS

$$\begin{pmatrix} \cdots \\ \cdots \\ \cdots \end{pmatrix}\begin{pmatrix} \cdots \\ \cdots \\ \cdots \end{pmatrix}\begin{pmatrix} \cdots \\ \cdots \\ \cdots \end{pmatrix} \cdots = \begin{pmatrix} & & \\ & ? & \\ & & \end{pmatrix}\begin{pmatrix} \cdots \\ \cdots \\ \cdots \\ \cdots \end{pmatrix}\begin{pmatrix} \cdots \\ \cdots \\ \cdots \\ \cdots \end{pmatrix}\begin{pmatrix} \cdots \\ \cdots \\ \cdots \\ \cdots \end{pmatrix} \cdots$$

$$P \sim X\, N$$

$$X \sim P\, N^{+}$$

Do this for all the behavioral states

RESULTS

Results given as a 3x3x4 tensor

If you are running and bump into standing crowd, you slow down or stop.

Current state

$$
\begin{array}{ll|ccc}
 & & \text{Non-moving} & \text{Random wandering} & \text{Forward moving} \\
\hline
\text{Next state} & \text{Non-moving} & \begin{pmatrix} 0.998633 \\ -0.00171597 \\ -0.000068283 \\ 0.00227864 \end{pmatrix} & \begin{pmatrix} 0.00673272 \\ 0.00536347 \\ 0.000270352 \\ -0.00245897 \end{pmatrix} & \begin{pmatrix} 0.00147674 \\ 0.023784 \\ 0.00120177 \\ -0.000409453 \end{pmatrix} \\
 & \text{Random wandering} & \begin{pmatrix} 0.00153507 \\ 0.000861908 \\ 0.000470325 \\ -0.00203876 \end{pmatrix} & \begin{pmatrix} 0.977766 \\ -0.00220219 \\ -0.00651538 \\ -0.00596974 \end{pmatrix} & \begin{pmatrix} 0.0300453 \\ 0.0428533 \\ -0.0051096 \\ -0.0104541 \end{pmatrix} \\
 & \text{Forward moving} & \begin{pmatrix} -0.000167797 \\ 0.000854058 \\ -0.000402042 \\ -0.000239876 \end{pmatrix} & \begin{pmatrix} 0.0155016 \\ -0.00316127 \\ 0.00624503 \\ 0.00842872 \end{pmatrix} & \begin{pmatrix} 0.968478 \\ -0.0666372 \\ 0.00390783 \\ 0.0108635 \end{pmatrix}
\end{array}
$$

Interactions

CONCLUSIONS

Proposed a framework for inferring individual behavioral state transitions from video recordings

- Interactive semi-automated tracking
- Detection of spatially/temporarily heterogeneous individual behaviors
- Modeling of behavioral transitions and interactions

Future steps:

- Simulation of behaviors using interaction tensor
- Conducting systematic evaluations
- Modeling more behaviors and nonlinear interactions

ACKNOWLEDGMENTS

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