Gaussian Process Regression Flow for Analysis of Motion Trajectories

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http://www.cc.gatech.edu/cpl/projects/gprf

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Goal and Motivation

A new representation for modeling and recognizing motion trajectories with incomplete motions and variations in sampling rates

1. Model a trajectory as a stochastic vector field
2. Supports matching of complex motions, predicting motion trajectories, and detecting anomalous events

Overview of Approach

1. Track moving objects from video
2. Learn patterns and construct stochastic fields in normalized spatio-temporal domain using Gaussian process regression (GPR)
3. During an on-line testing of a trajectory,
   - Incrementally predict possible paths by matching on-line trajectories to learned patterns
   - Detect an anomalous trajectory by calculating its likelihood and ambiguity using excess kurtosis

Trajectory to stochastic field

Approximation using GPR

$$p(y^* \mid x^*, \mathbf{x}, \mathbf{y})$$

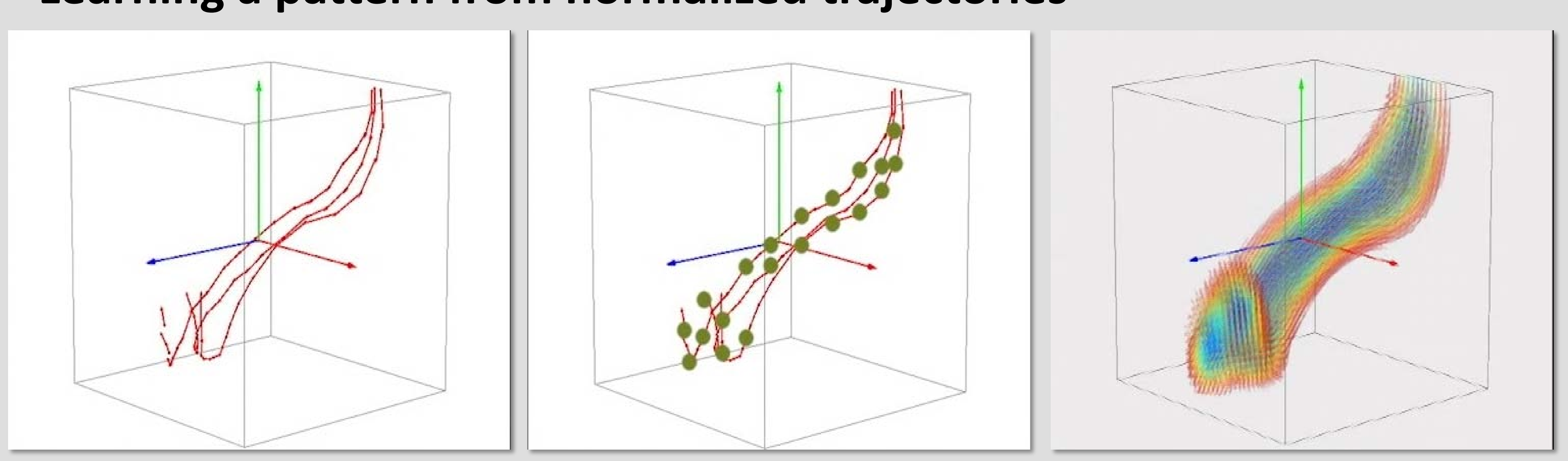
Mean → Approximation
Var → certainty (confidence)

y* : output variable
x* : evaluating point
x : training samples
y : sample velocities

$$\Phi(x) = \bar{y}^*_u(x)\mathbf{i} + \bar{y}^*_v(x)\mathbf{j} + \bar{y}^*_t(x)\mathbf{k}$$

: Gaussian process regression flow (GPRF)

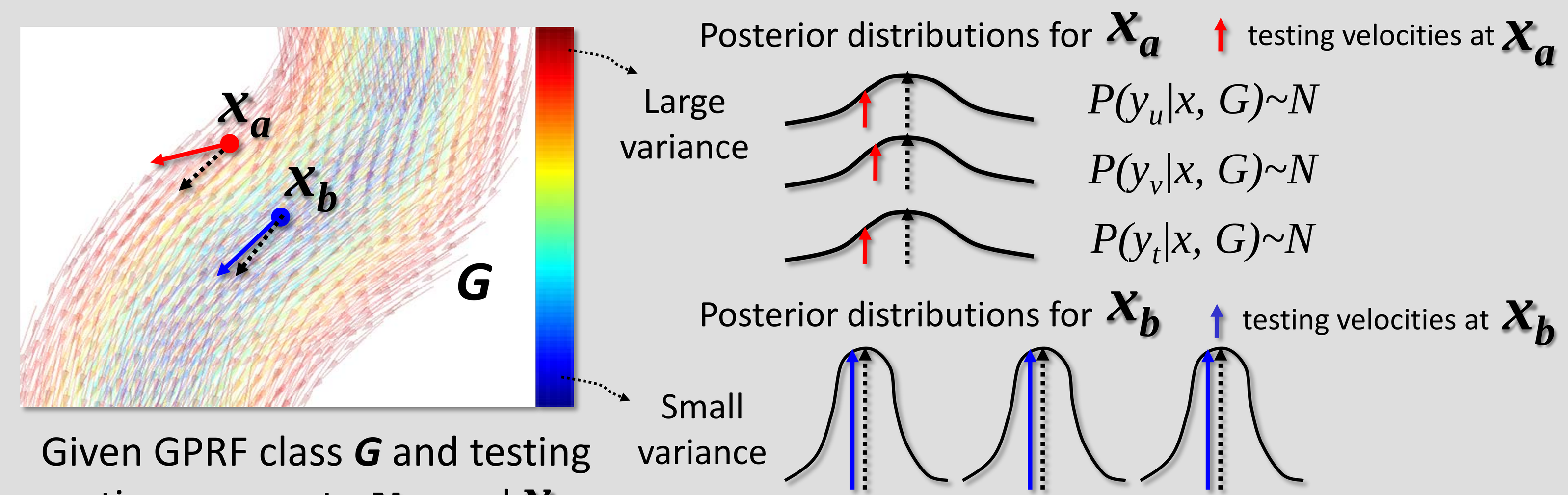
Learning a pattern from normalized trajectories



Trajectories in spatial and **normalized[1]** temporal (t) domain → Sample trajectories for balancing stable variance distribution over other classes → Generated GPRF

(1: Lin et al. SIGMOD '03)

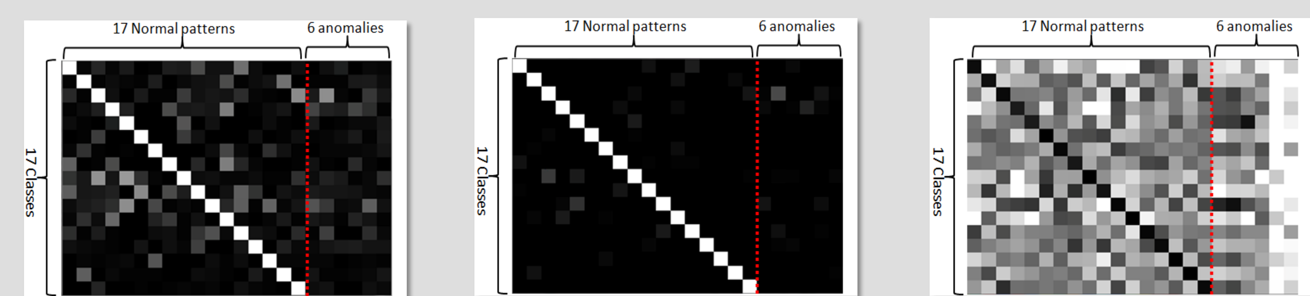
Similarity Measurement



Given GPRF class *G* and testing motion segments x_a and x_b

1. Compute the local likelihood for class *k* from posteriors
2. Compute global likelihood by weighted summation of local likelihood for each class

Similarity testing using 17 classes with 17 normal patterns and 6 anomalous tracks

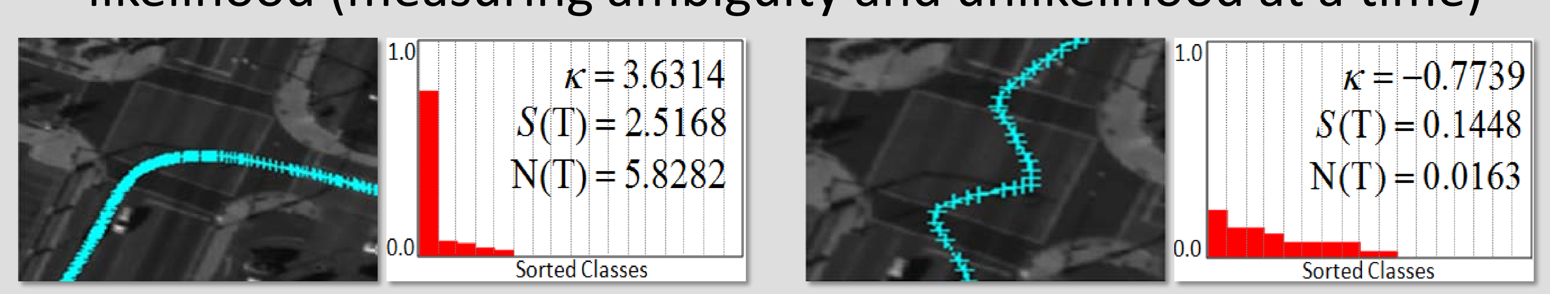


Local Likelihood only | Global Likelihood | Derivative dynamic time warping

3. Prediction from incomplete trajectory
   Finding a temporal scale that maximizes the likelihood

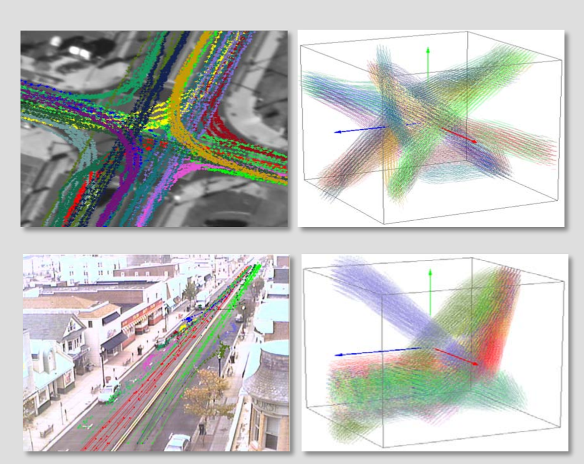
Anomaly Detection

1. Measuring Excess Kurtosis (EK) from the distribution of each local probability to be a specific class
2. Then, normality function N is calculated from EK and global likelihood (measuring ambiguity and unlikelihood at a time)



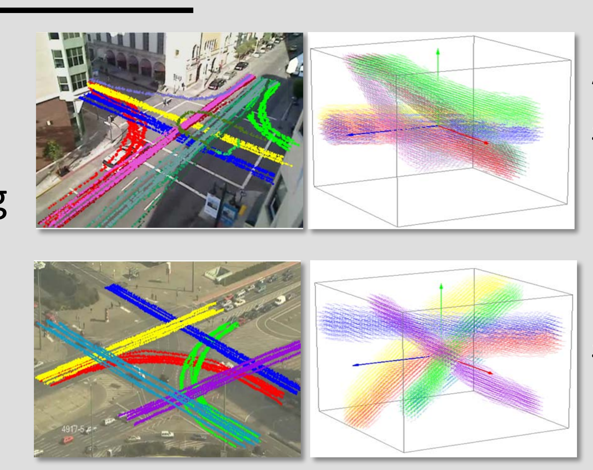
Normal pattern | Anomalous pattern

Datasets



CLIF Data
#class : 17
FPS: Varying

Ocean City
#class : 11
FPS: 5

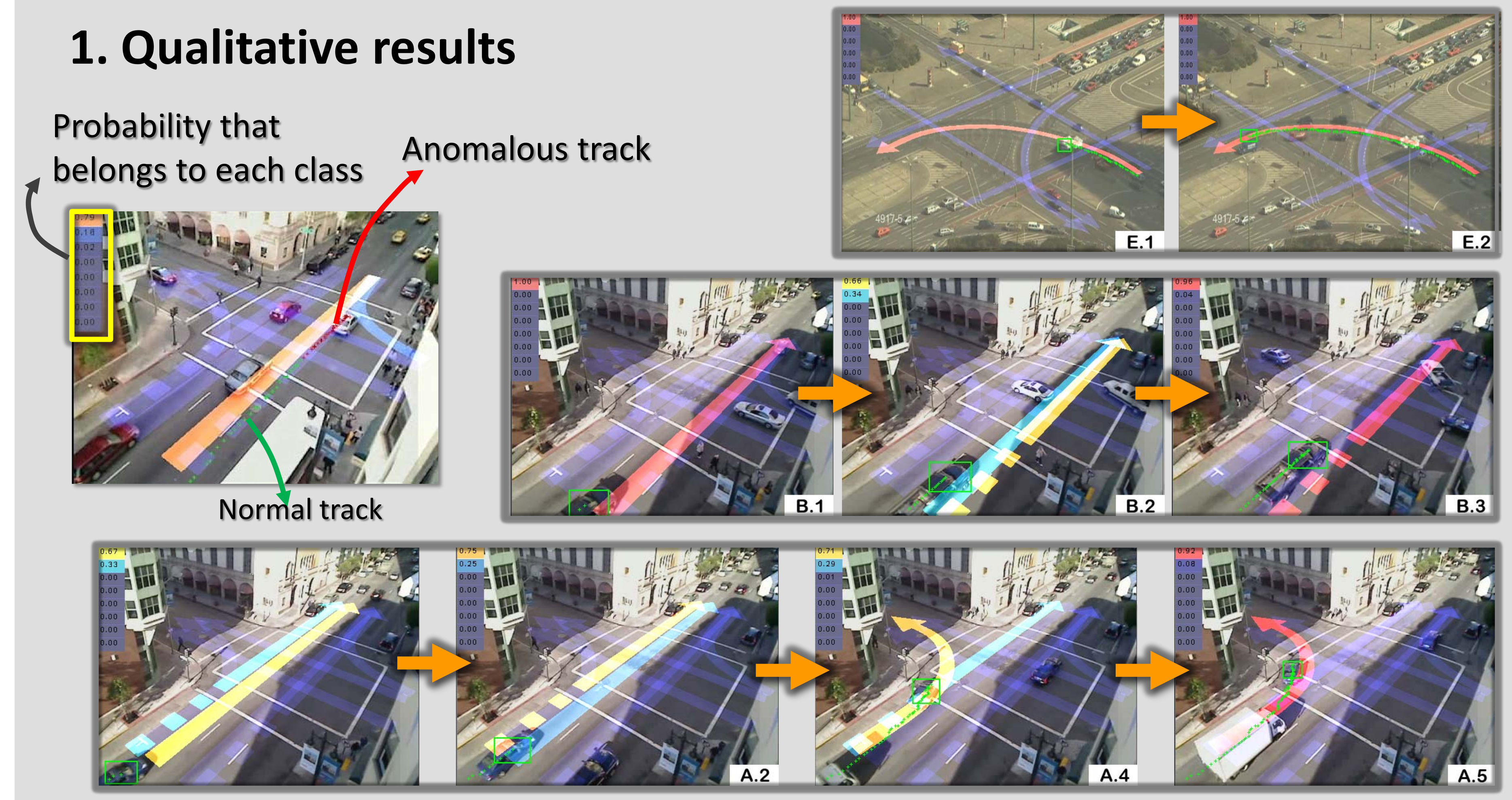


Adam Data
#class : 8
FPS: 10-30

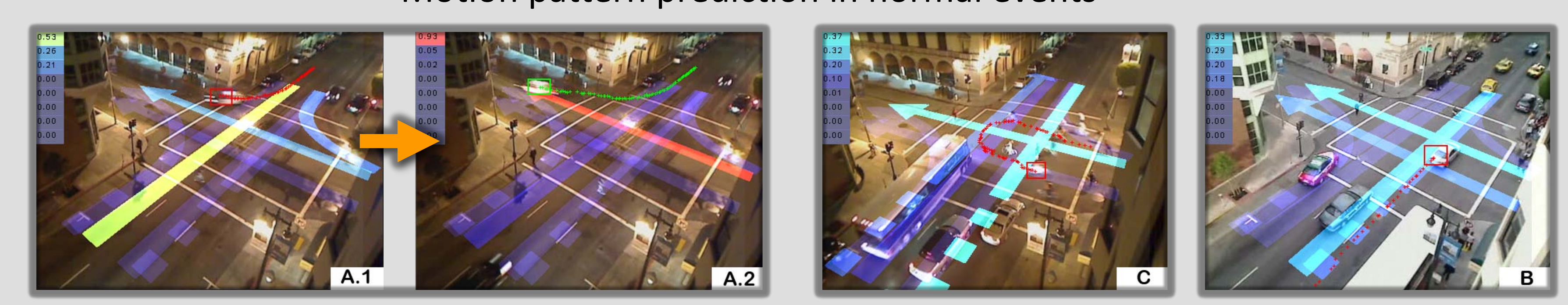
UCF
#class : 6
FPS: 30

Results & Evaluation

1. Qualitative results



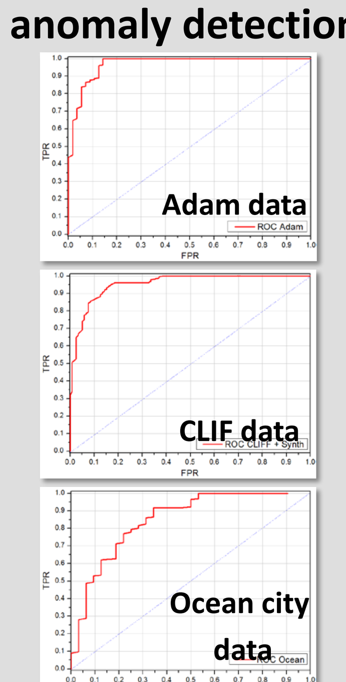
Motion pattern prediction in normal events



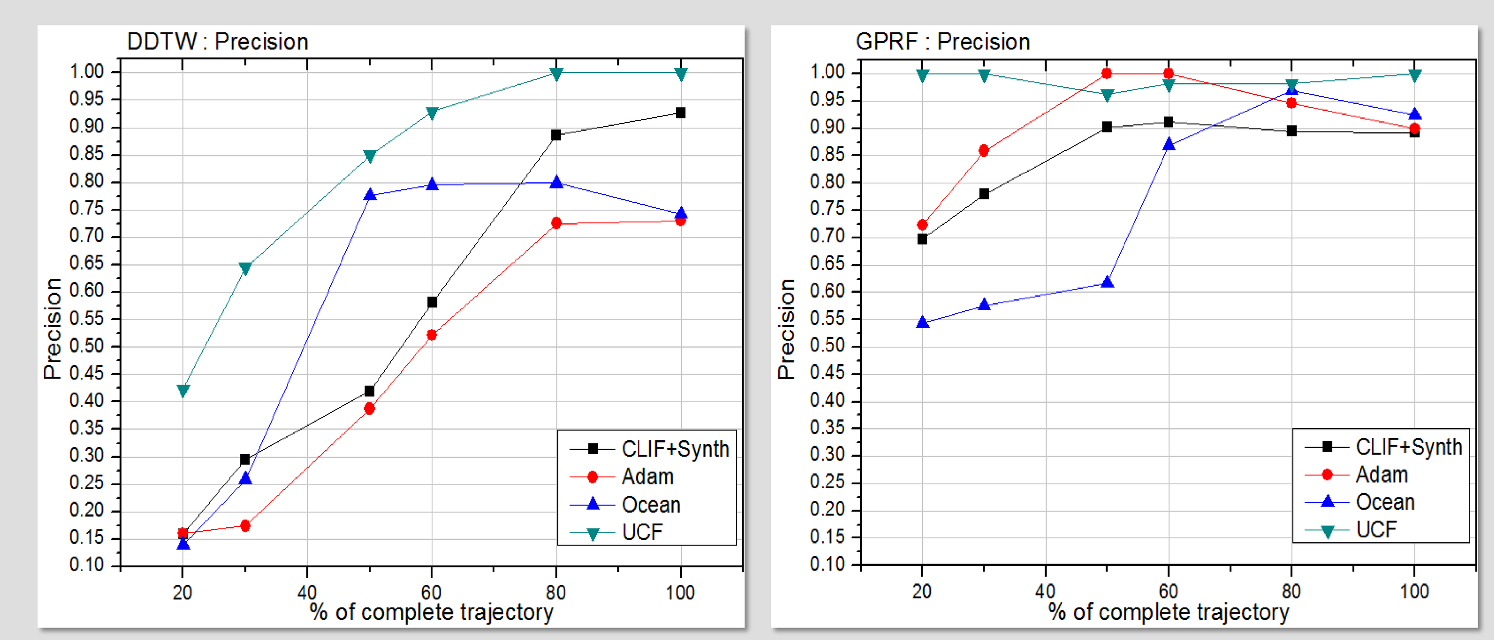
Anomalous event detection (red trajectories)

2. Quantitative Evaluation

ROC for anomaly detection



Precision of classification using incomplete motions



Precision with DDTW | Precision with GPRF

Conclusion

1. A novel framework for modeling motion trajectories in stochastic motion field using Gaussian process regression
2. Effectively recognize motion patterns from both complete and incomplete tracks even with variations in sampling rates

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