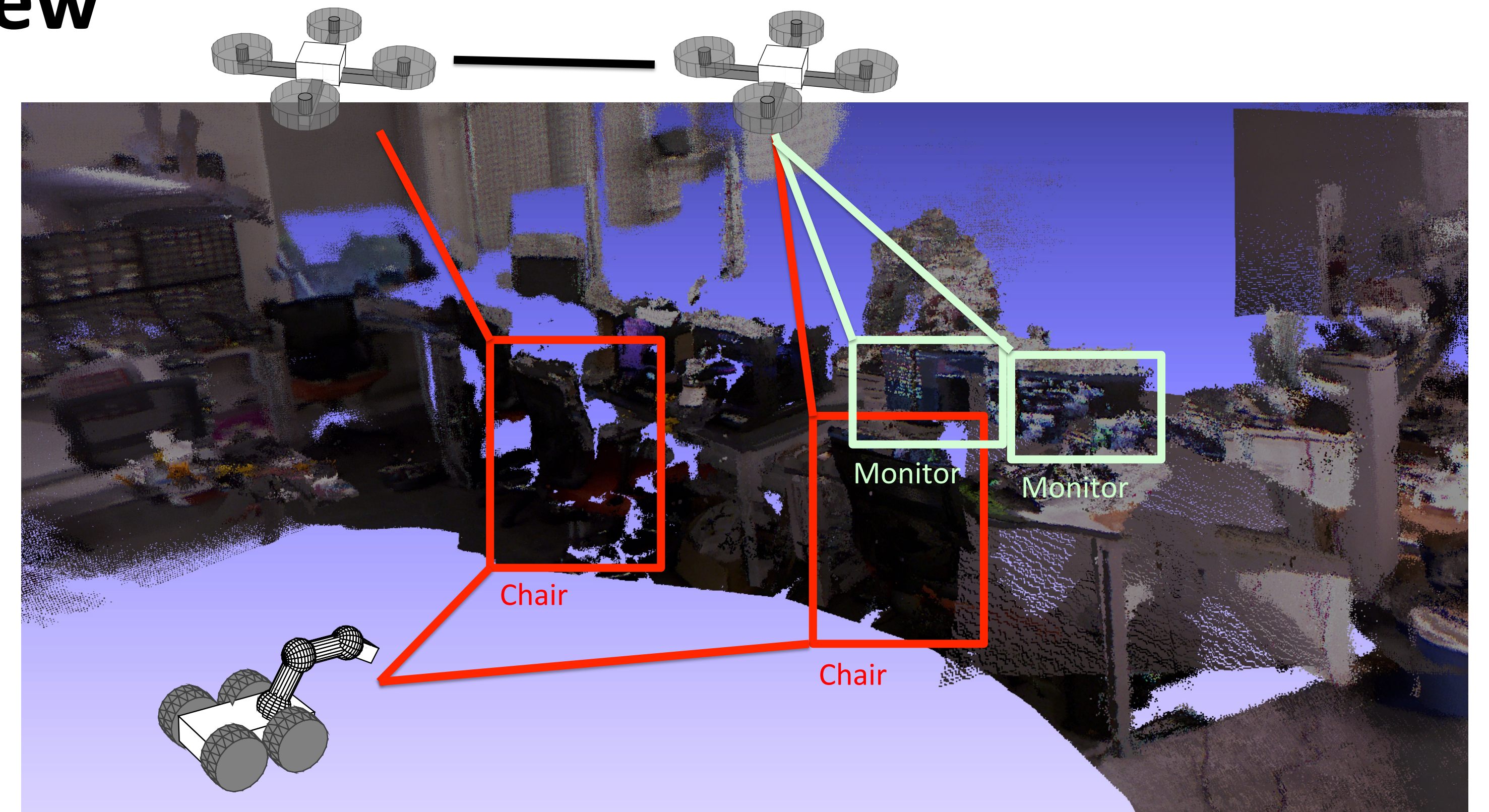


Overview

Goal: enable multiple co-robots to robustly and efficiently map and understand the environment on a **semantic level**

- Multiple heterogeneous robots share measurements and computational resources
- Incorporate semantic information (object detections) into mapping, enabling new types of measurements and richer maps that can be easily interpreted by humans
- Use the redundancy contained in cycles of multiple measurements to detect and correct inconsistencies
- Make intelligent use of the available resources through approximate computing



Statistical outlier identification through E.-M. and Belief Propagation

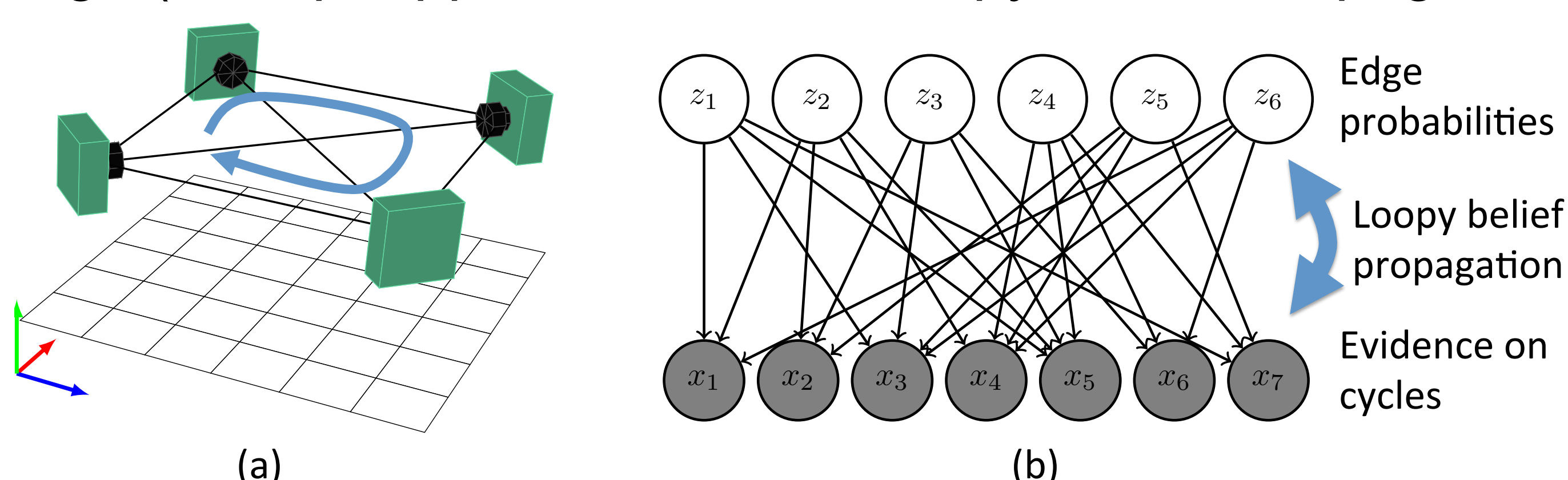
Motivation: In modern mapping solutions, it is often necessary to find links between different parts of a dataset, e.g., to handle tracking losses due to fast motions, loop closures. Object detections provide additional measurements and constraints.

Goal: Obtain robust correspondences across parts of the map, despite perceptual aliasing (outliers), and provide localized estimates of the probability of errors.

Principle: Exploit the redundancy contained in cycles of measurements, and use Expectation Maximization for estimating the probability that each measurement is an outlier

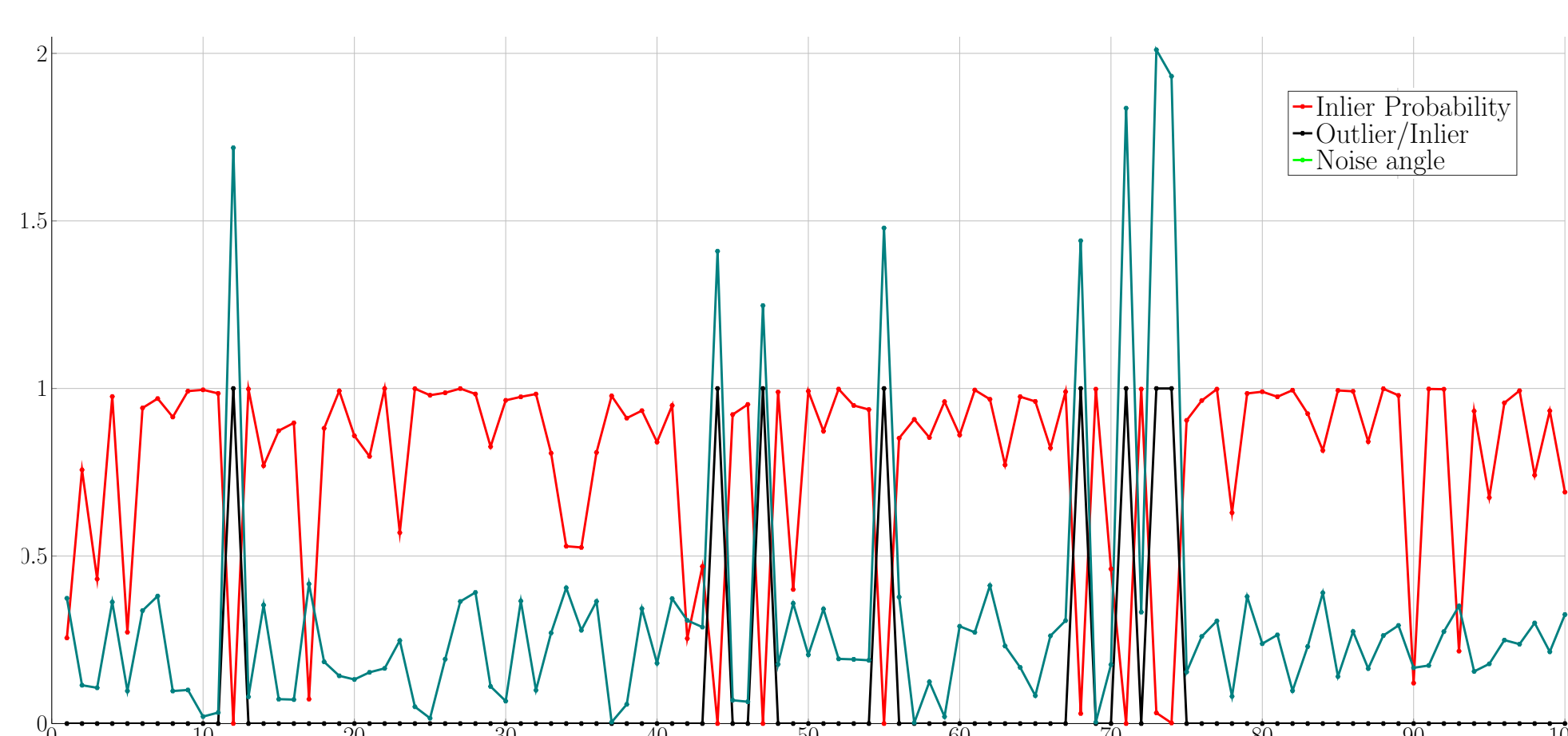
Basic example: estimate absolute rotations from relative ones.

- *Evidence:* closure error on cycles (assumes Gaussian noise).
- *Inference:* estimate the covariances for inlier/outliers (M-step), together with the probability of outliers on each edge (E-step, approximated with loopy Belief Propagation).



For instance, in a complete graph with 4 nodes there are 6 independent cycles (a), leading to a Bayesian model (b).

Results: We can perform accurate inference in a scalable and robust manner (e.g., 25 nodes, 100 edges, 76 cycles, <1min)



Flexible approach: it is applicable to both continuous (rotations, translations) and discrete (object detection) measurements

Work in progress:

- Testing on mapping datasets including object detections
- Computational method to find out, *a priori*, whether for any given graph and outlier distribution, the outliers are uniquely identifiable (i.e., the true solution is recoverable).

Approximate computing

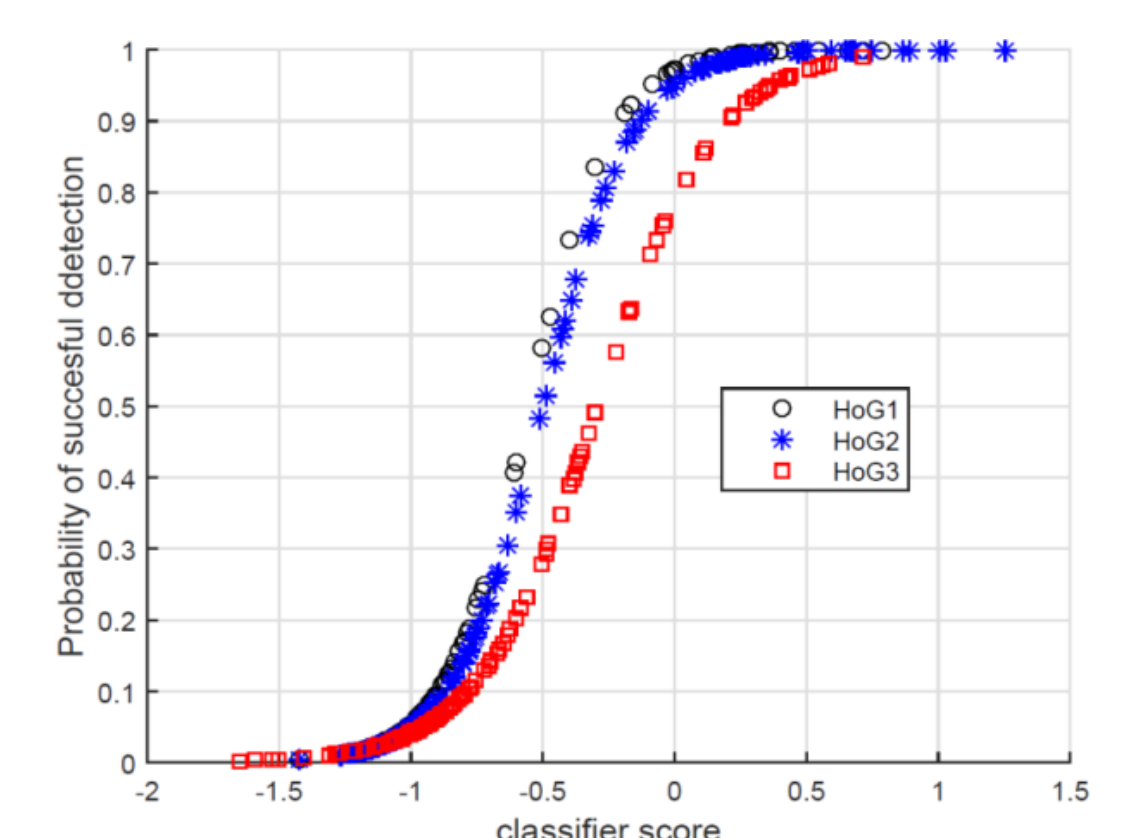
Goal: Bridge the gap between *computation-intensive* computer vision applications (object detection) and *resource-limited* and *uncertain* computation environments

Principle: Approximate computing = dynamically change parameters of algorithm to different accuracy/computations

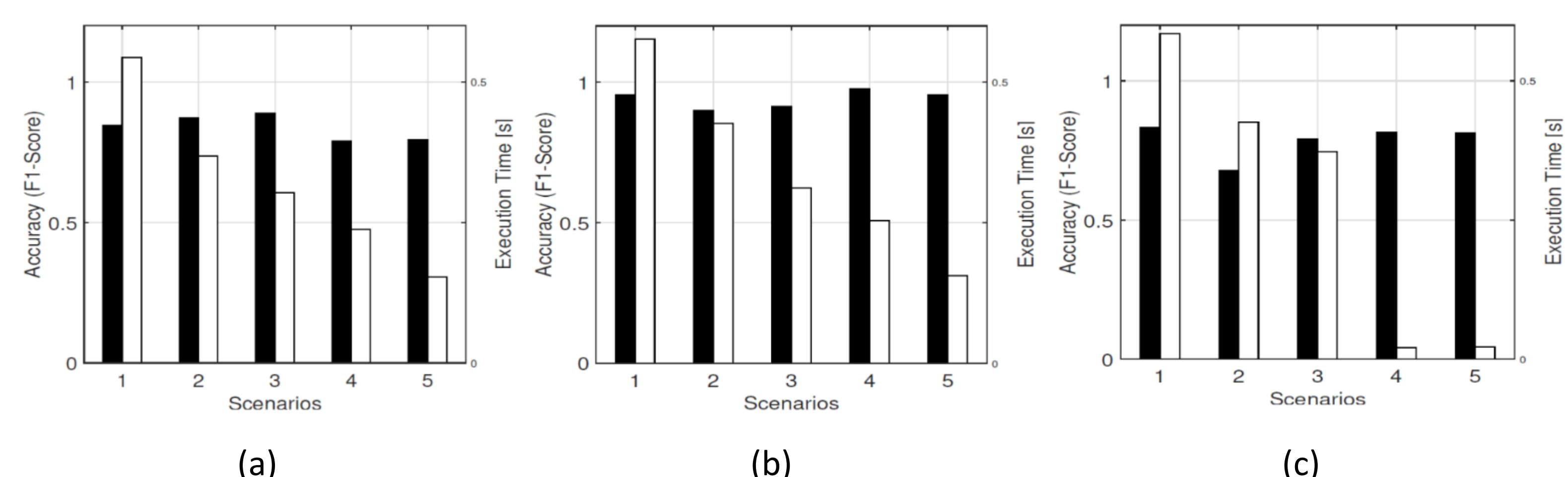
- Identify parameters dynamically depending on input, minimum desired accuracy, computational resources
- Exploit temporal correlation between frames

Technical approach: Offline learning + MDP + detection/tracking

- Identify offline parameters (e.g., number of object proposals) that can increase speed with a tolerable loss of accuracy
- Identify correlation between classifier score and actual performance
- Learn selection policy based on a Markov Decision Process
 - *State:* classifier score, current parameter selection
 - *Actions:* choice of parameters among Pareto-optimal set
 - *Reward:* ratio between classifier score and time
- Compute parameters at the beginning, then change based on estimated performance (classifier score)
- Integrate object tracking with object detection to speed up



Results: Decrease in execution time by 20-70% for accuracy of 100-98% on video datasets



- Scenarios: (1) Fixed parameters, (2) Random parameter selection, (3) MDP-based detection on each image, (4) Fixed parameter with tracking, and (5) MDP with tracking
- In images with *low clutter* (Fig. a), *high clutter* (Fig. b), and *poor illumination* (Fig. c), MDP (Scenario 3) performs better than fixed-parameter approach (Scenario 1)