Overhead Projection Approach For Multi-Camera Vessel Activity Recognition

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Introduction

Video feeds can help curb piracy and illegal fishing in maritime scenarios.

- **Cameras are cheap and easy to install.**
- Petabytes of video sensor data is not automatically analyzed in current scenarios
  - real time monitoring crew
- **By the time crew spots a suspicious vessel in the video sensor or from the ship, it is usually too late to react.**

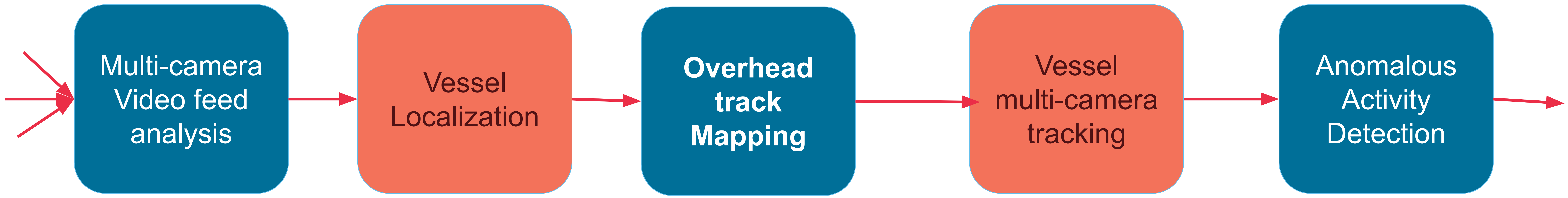
- There is no principled early warning system on big ships for suspicious activity of surrounding vessels.

Motivation

- Overhead imagery analytics are gaining importance in integrated maritime surveillance due to an increase in naval traffic, a decrease in crews on the decks of large ships, and an increase of maritime piracy and illegal fishing.
- Maritime piracy attacks have cost the industry billions of dollars, and these attacks pose significant danger to the crew members aboard.
- The use of visual data feeds provides an increasingly viable method of identifying potential threats along with the other onboard sensors.
- Automated AI systems which use visual feeds and other on board sensors can serve as an early warning threat detection system

Contribution

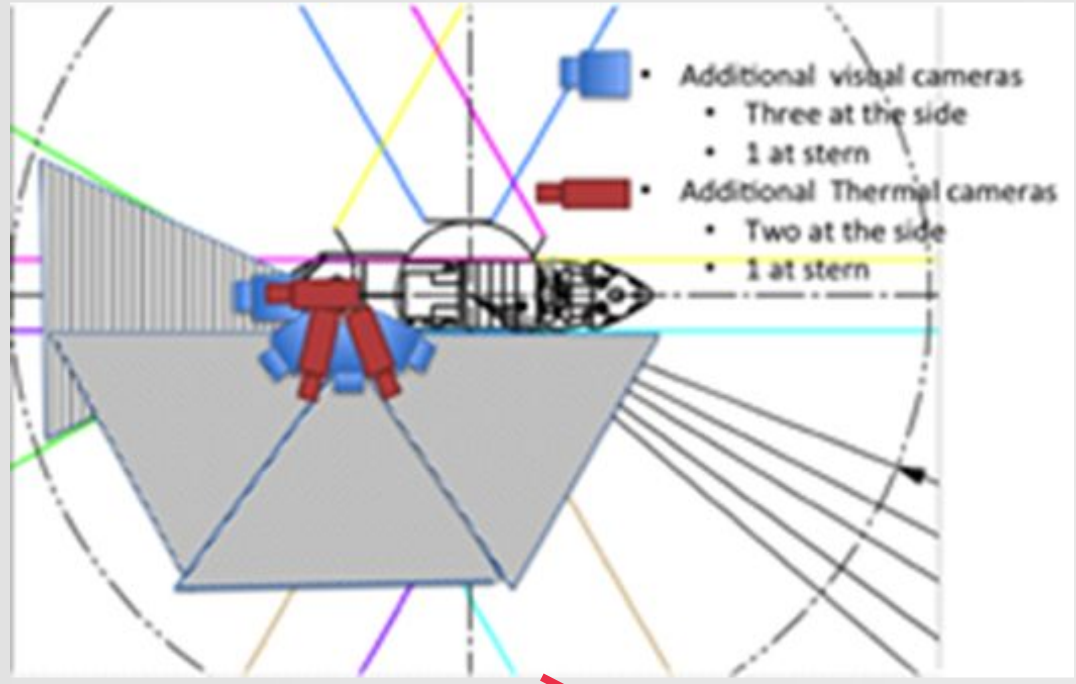
- End-to-end system that
  - ***analyzes*** multi-camera ship video feed,
  - ***localizes*** maritime vehicles in the video feed,
  - ***identifies*** the maritime vehicle over multiple cameras,
  - ***maps*** the vehicle track onto an overhead plane, and
  - ***detects*** anomalous vessel movement around the ship.



Contribution

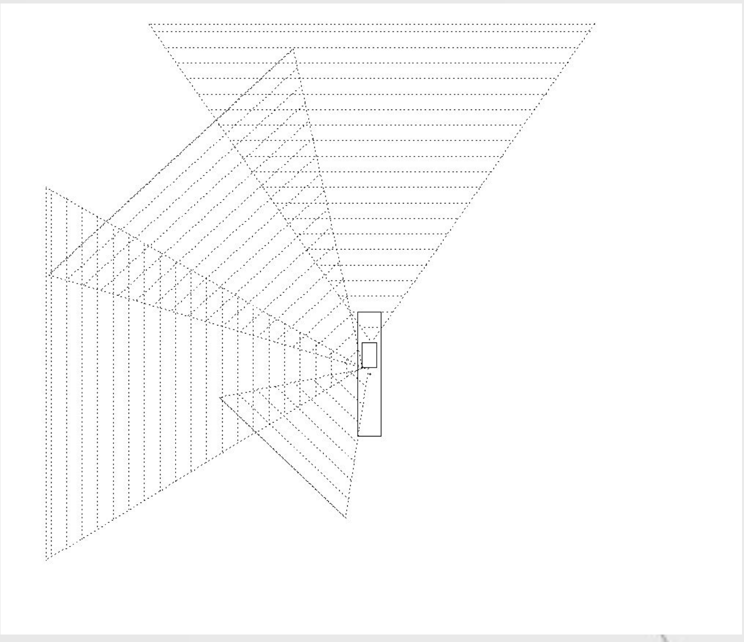
- Synthetic Data Generator
- Propose and compare three novel modes of trajectory analysis and activity classification:
  - Computing with Words (CWW),
  - Markov trajectory feature classifier (MTFC),
  - Naïve Bayes Radial Classifier (NBRC)

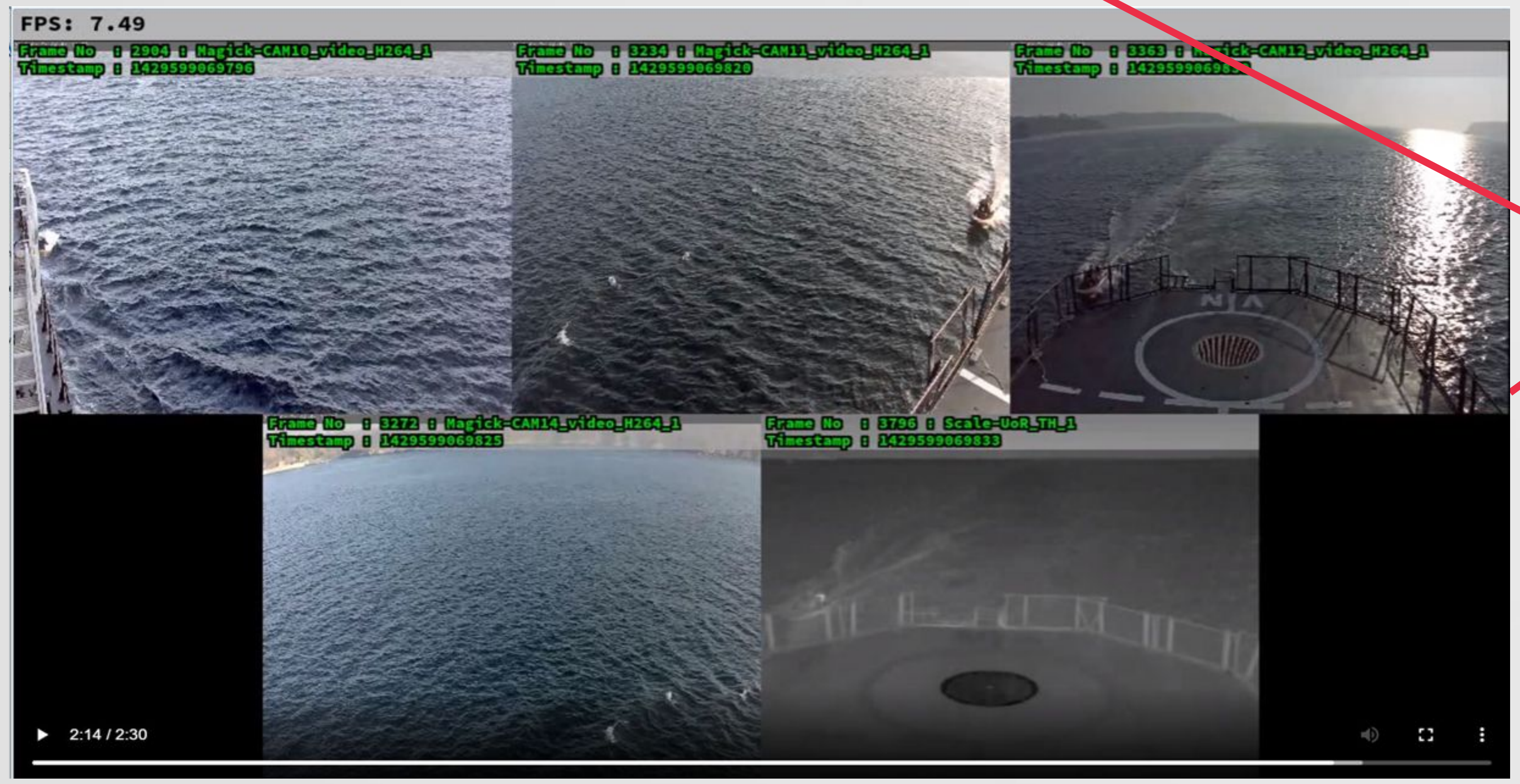
Multi-camera Video Feed Analysis



Positions of the cameras;
size + types of vessels;
types of activities;
mission objectives

overhead plane construction





Multi-camera Video feed analysis

- synthetic data creation parameters
- Deep Neural Network Model and Training Approach

Vessel Localization

- DNN selection
- Model Training
- Model Domain Adaptation

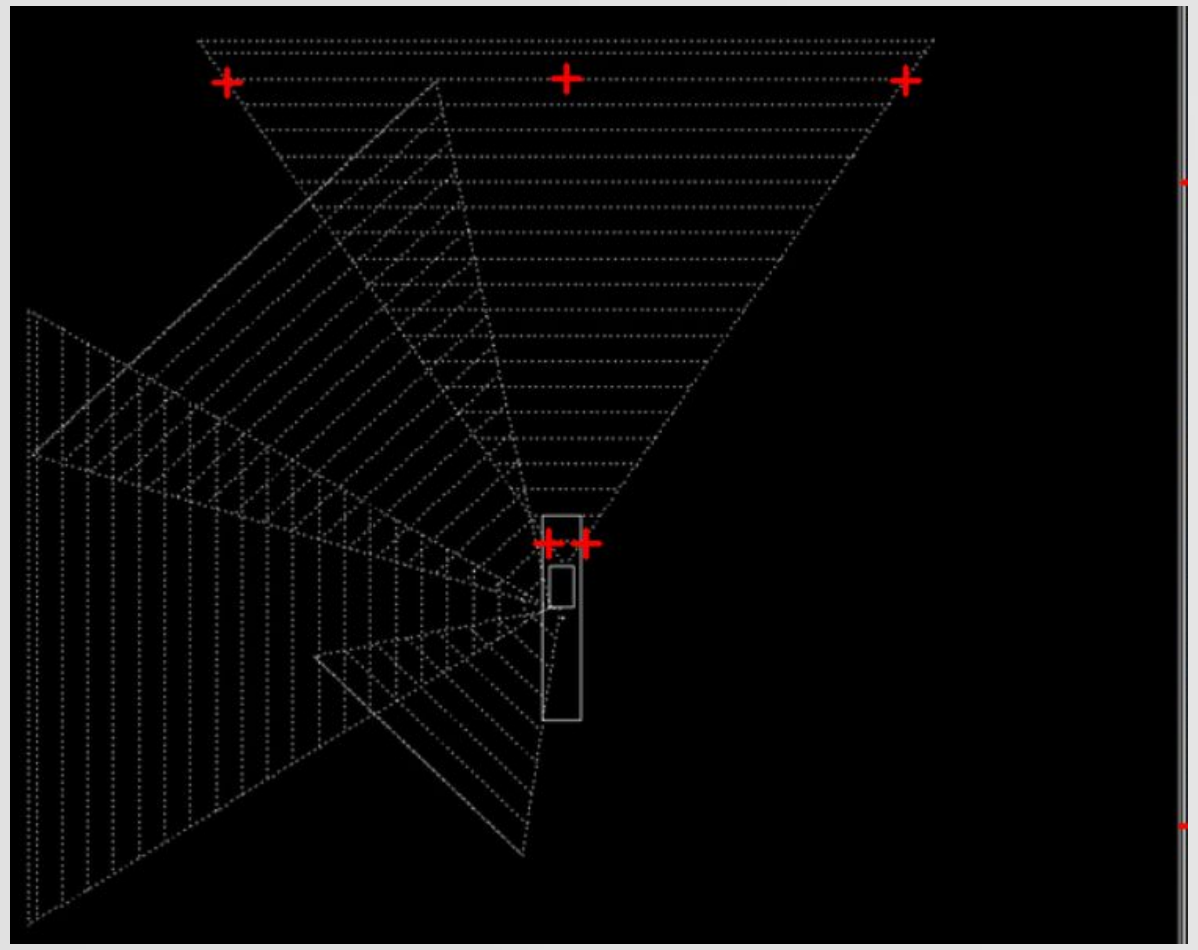
Vessel Localization

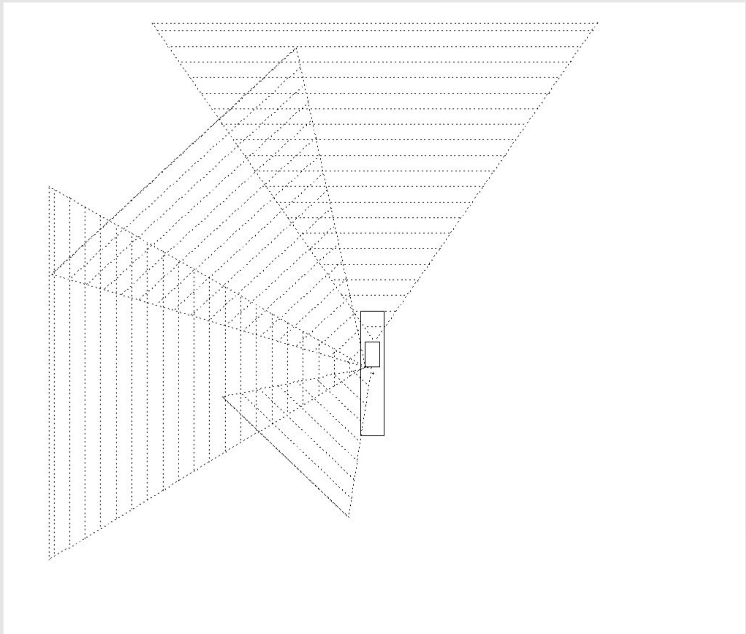
- Object Localization and Labeling
- High recall

N. Warren, B. Garrard, E. Staudt and J. Tesic, "Transfer Learning of Deep Neural Networks for Visual Collaborative Maritime Asset Identification," *2018 IEEE 4th International Conference on Collaboration and Internet Computing (CIC)*, 2018, pp. 246-255, doi: 10.1109/CIC.2018.00041.

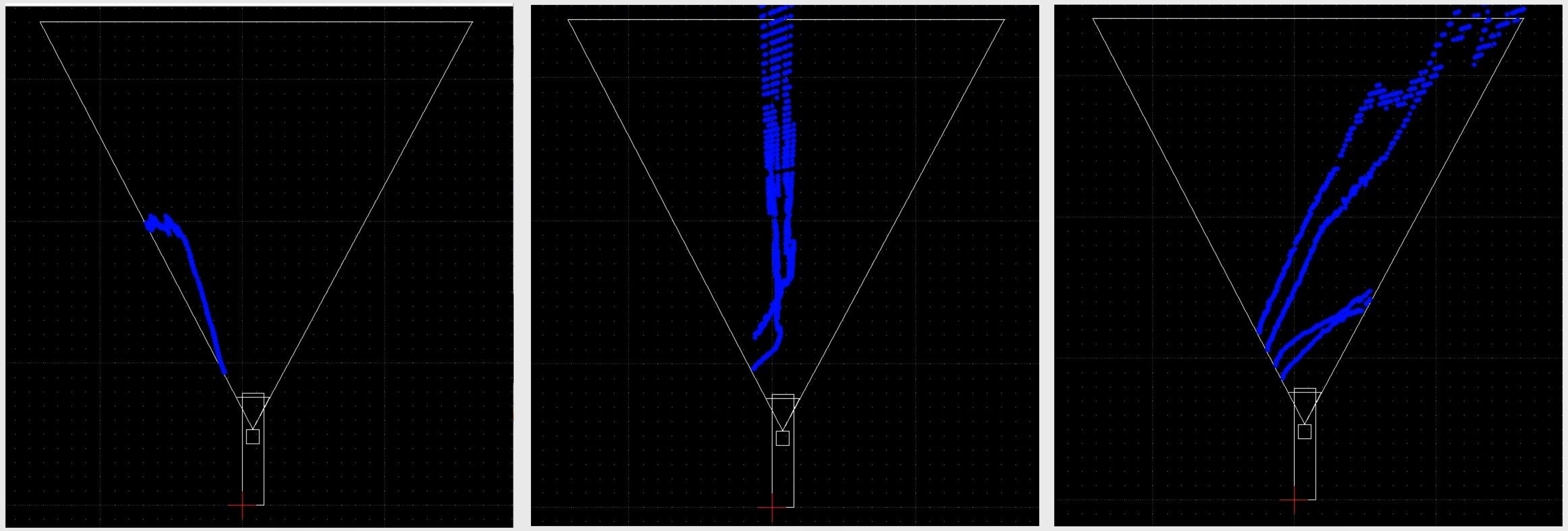
Overhead Track Mapping

- Transform coordinate relevant to different cameras into coordinate relevant to our ship (overhead projection).
- Ship is the center of the coordinate system
- The mapping of the coordinates relevant to the cameras into the coordinates of the overhead projection.



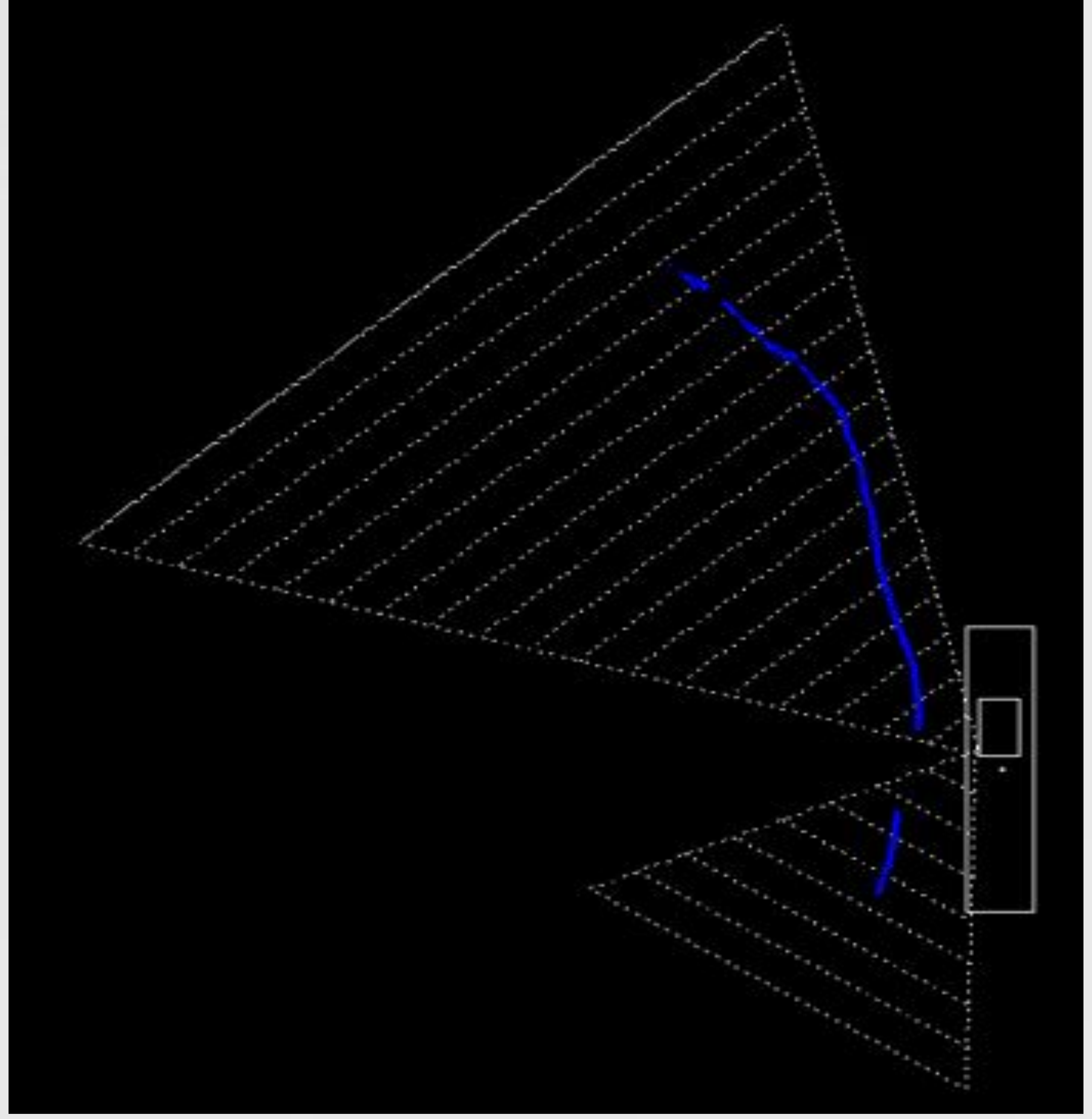


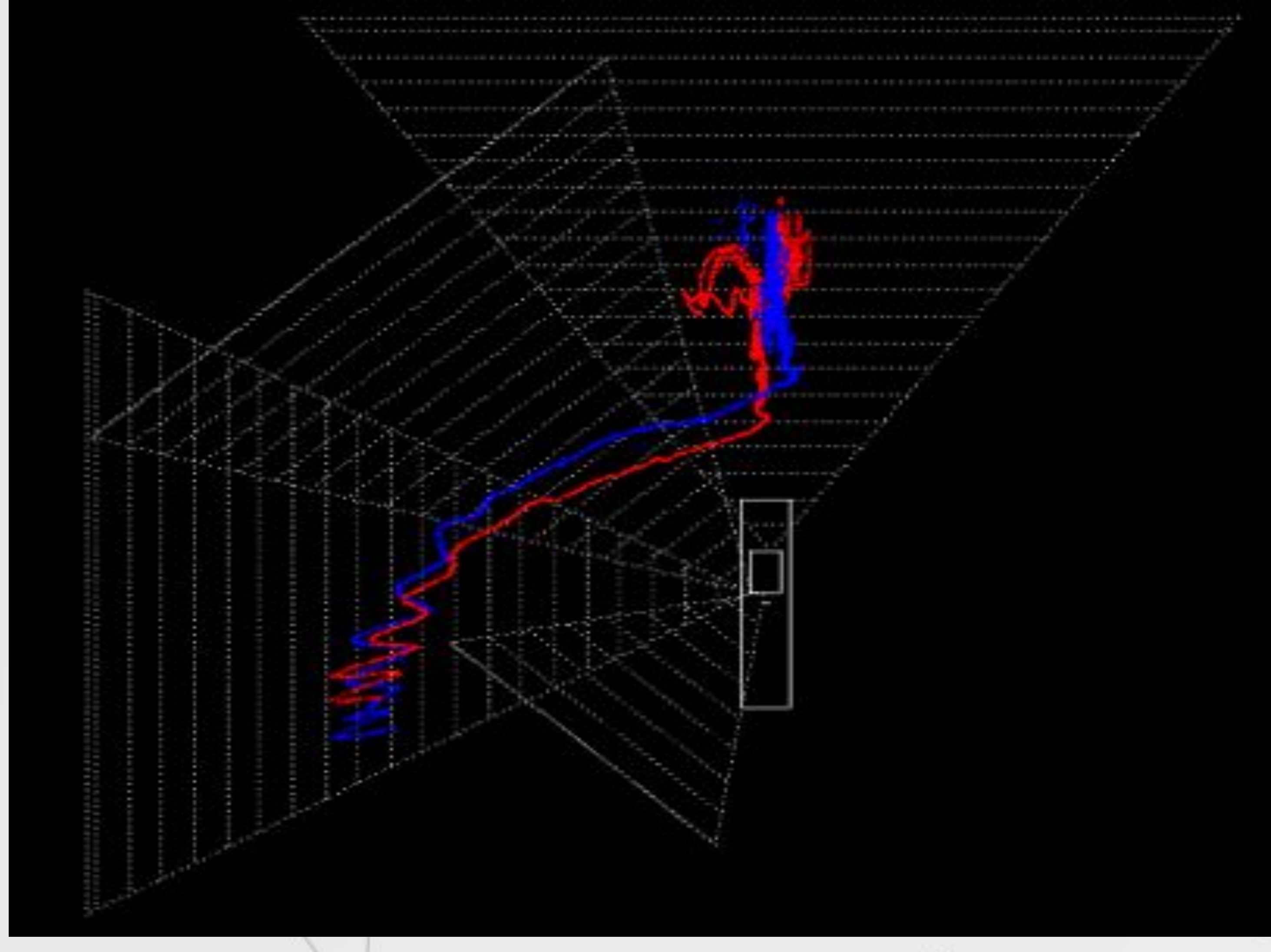
Overhead track Mapping

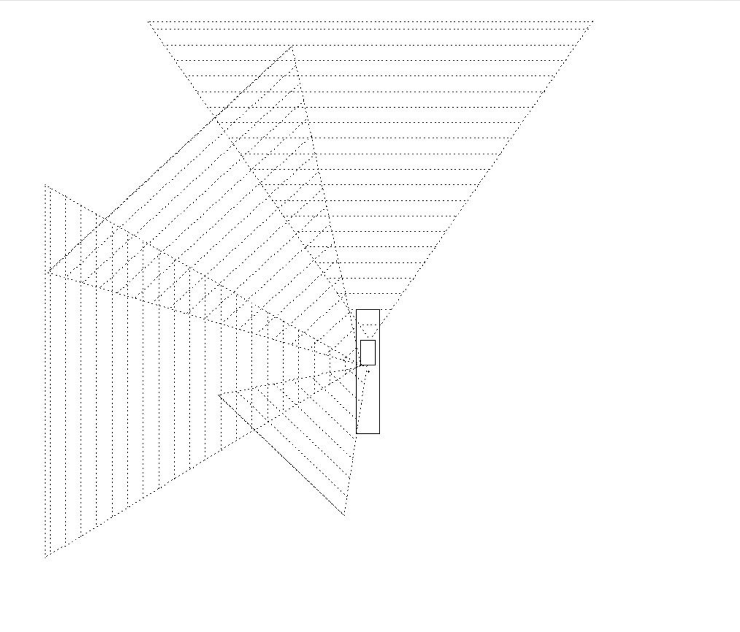


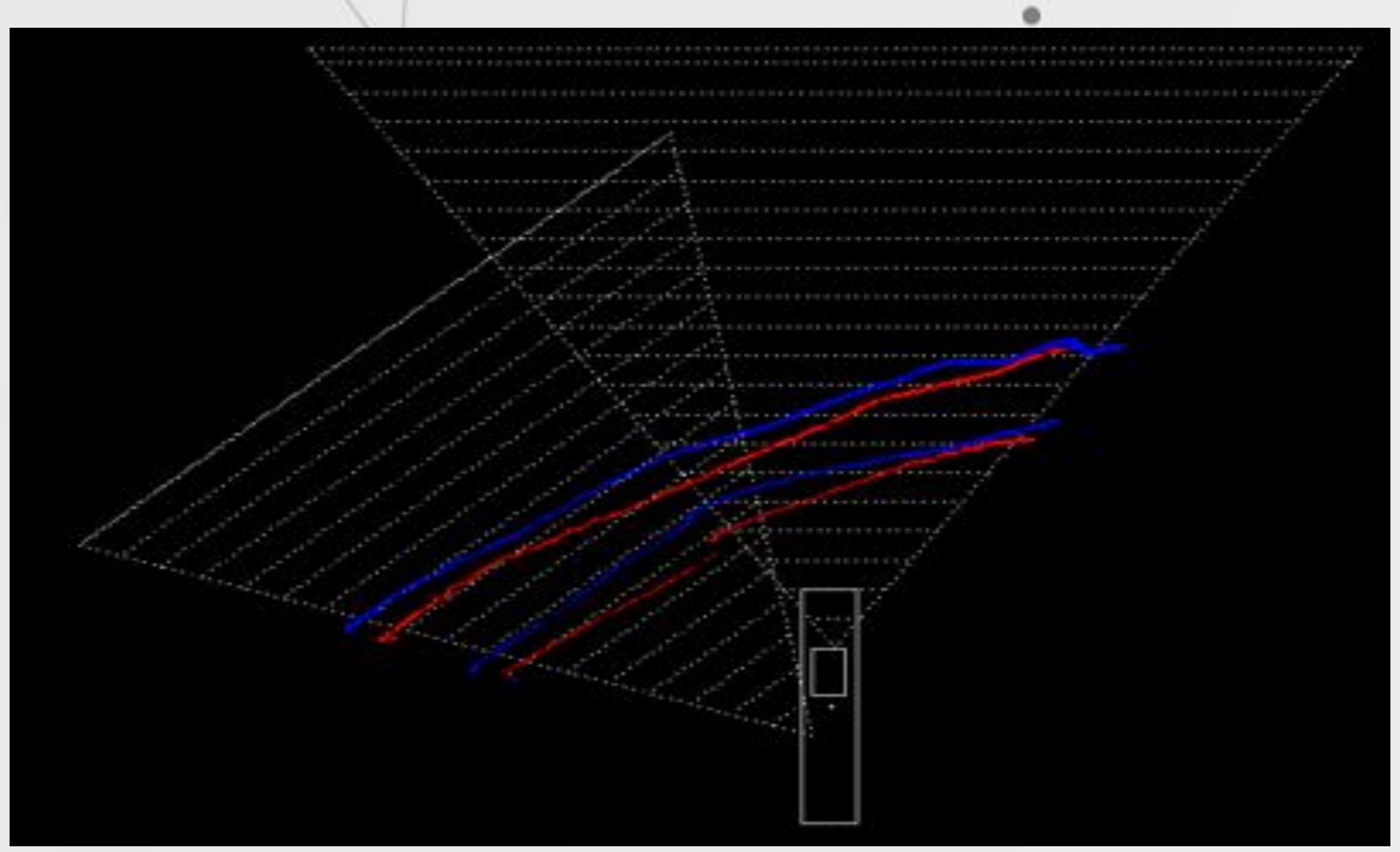
Multi-camera tracking

- Connect tracklets to tracks (relabeling vessels identified) from all cameras using visual similarity, camera location, and spatio-temporal information across video streams.
- Represent tracks in overhead system







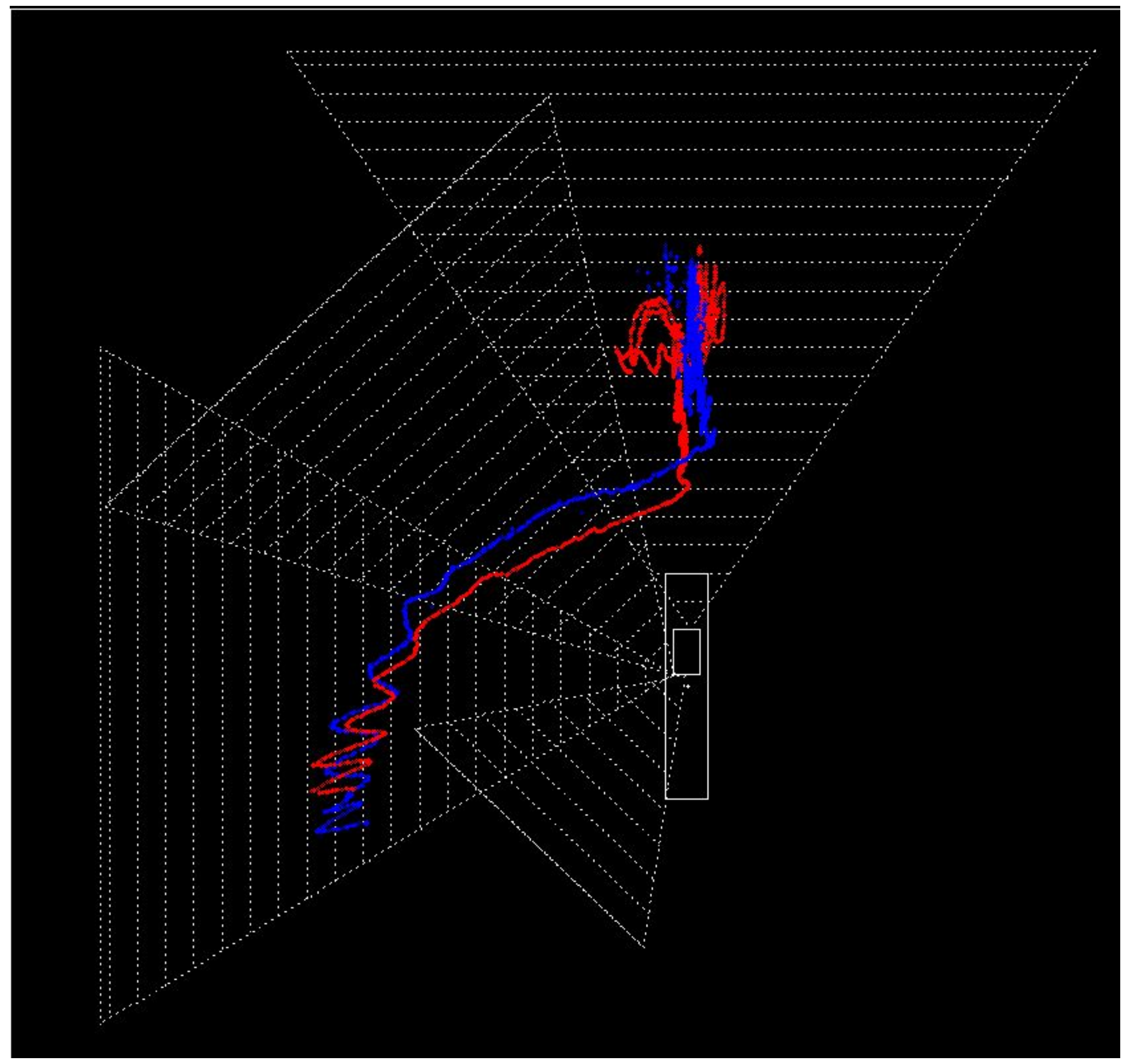


- Object re-labeling based on camera position
- Connecting tracks to tracklets

Vessel multi-camera tracking

- Object Tracking across multiple cameras

Track Activity Detection: standardizing trajectories



Trajectories in the overhead plane are recorded as a list of pixel locations on the overhead image in discrete time intervals.

- Since activities can take place over a wide variety of time domains, trajectories are normalized by distance, not time duration.
- Normalization is done by iterating backwards over the previous points until a distance threshold is met.
- The trajectory is then given a set number of points using k-means which reduces noise and sets makes every model we evaluate have the same number of points

Track Activity Detection

Paper Contribution

- Synthetic Data Generator
- Propose and compare three novel modes of trajectory analysis and activity classification
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Anomalous Activity Detection

Synthetic Data Generator

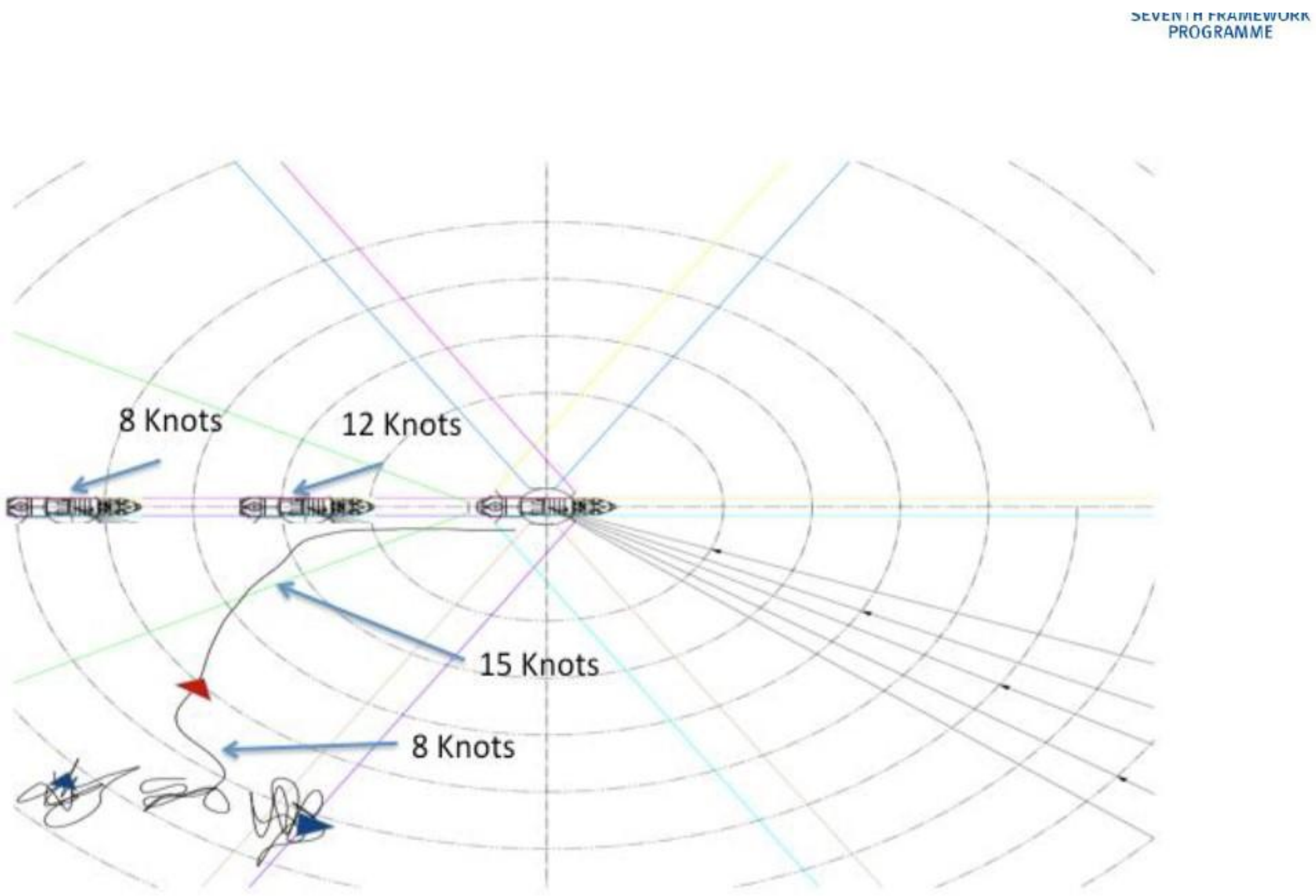


Figure 11 : Schematic representation for the first pirate attack scenario on open sea. Skiff boat is represented in red. Tracking micro-scenarios 'Approach' and 'Changing appearance' are likely to occur.

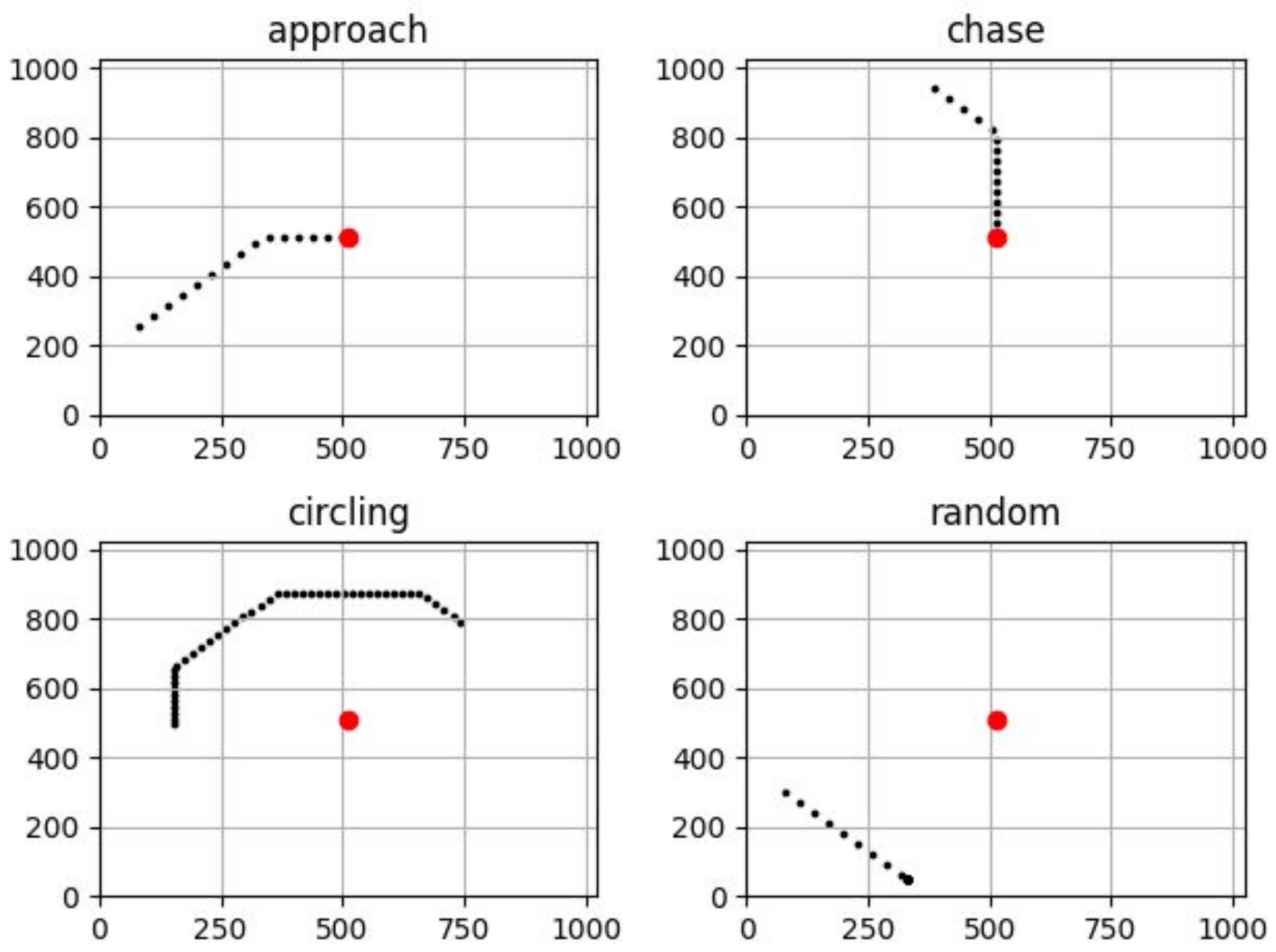
IPATCH data (http://www.ipatchproject.eu/) is only known real piracy model.

- Provides description of activities that are anomalous (e.g. following circling appraching)
- We annotated trajectories of the vessels and their activities
- **Too small** (under 5 examples per activity, many single camera only)

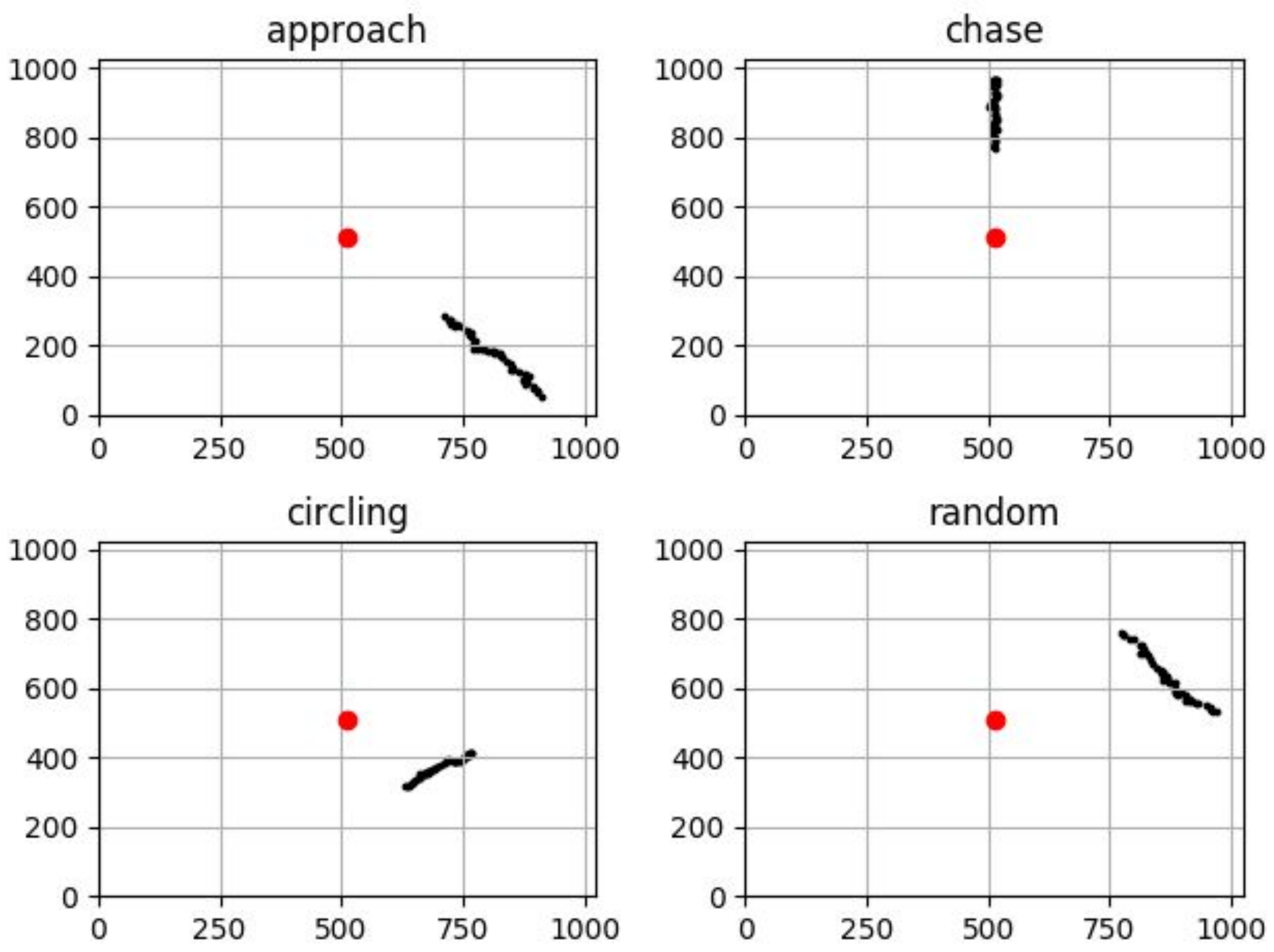
Synthetic Data Generator

Create a synthetic dataset inspired by IPATCH activity definition and trajectories.

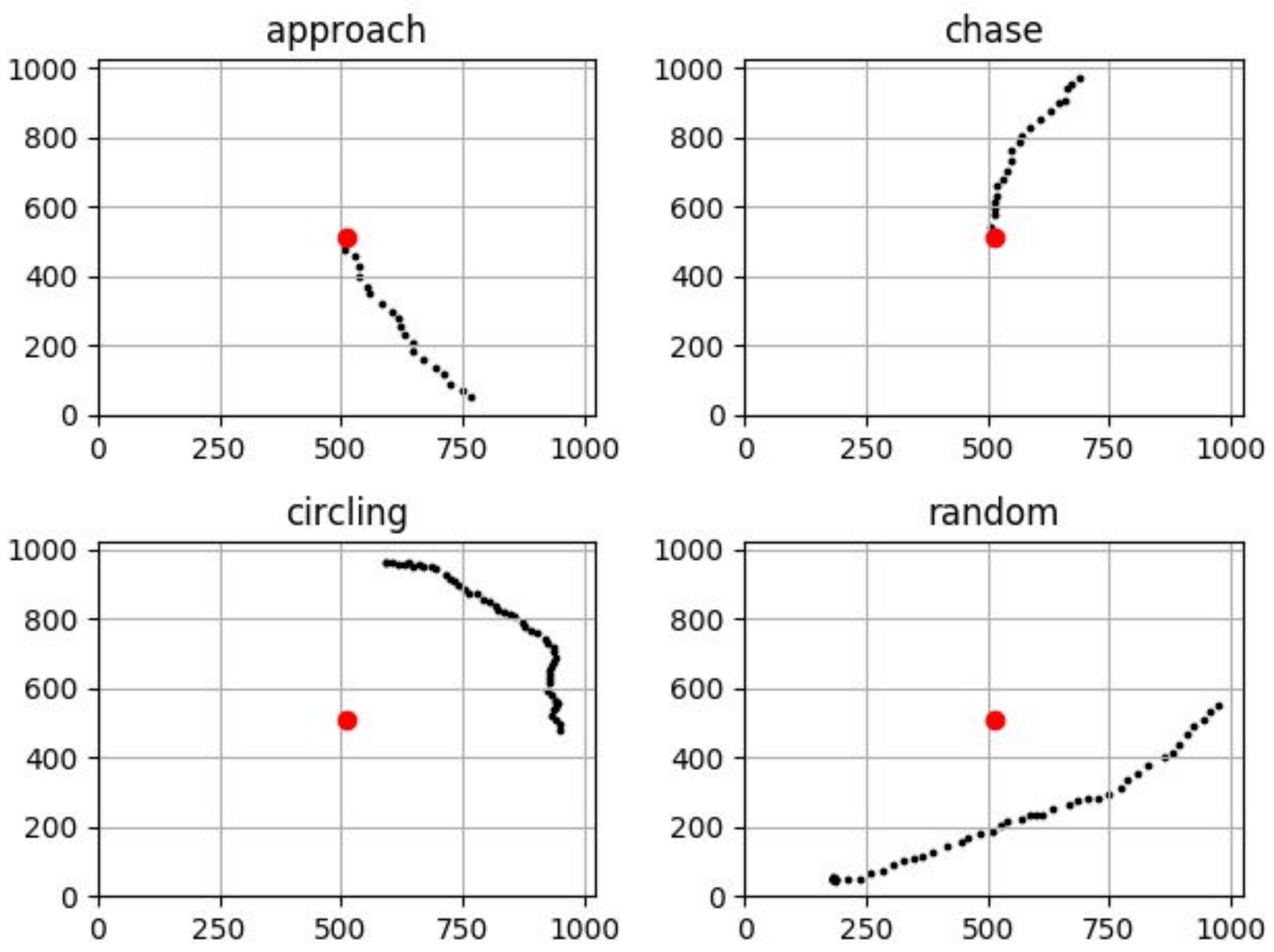
No noise
PD: [100, 0, 0, 0, 0, 0, 0, 0, 0]



Too much noise
PD: [20, 10, 10, 10, 10, 10, 10, 10, 10]



Consistent with observed data
PD: [20, 15, 15, 10, 10, 10, 10, 10, 0]



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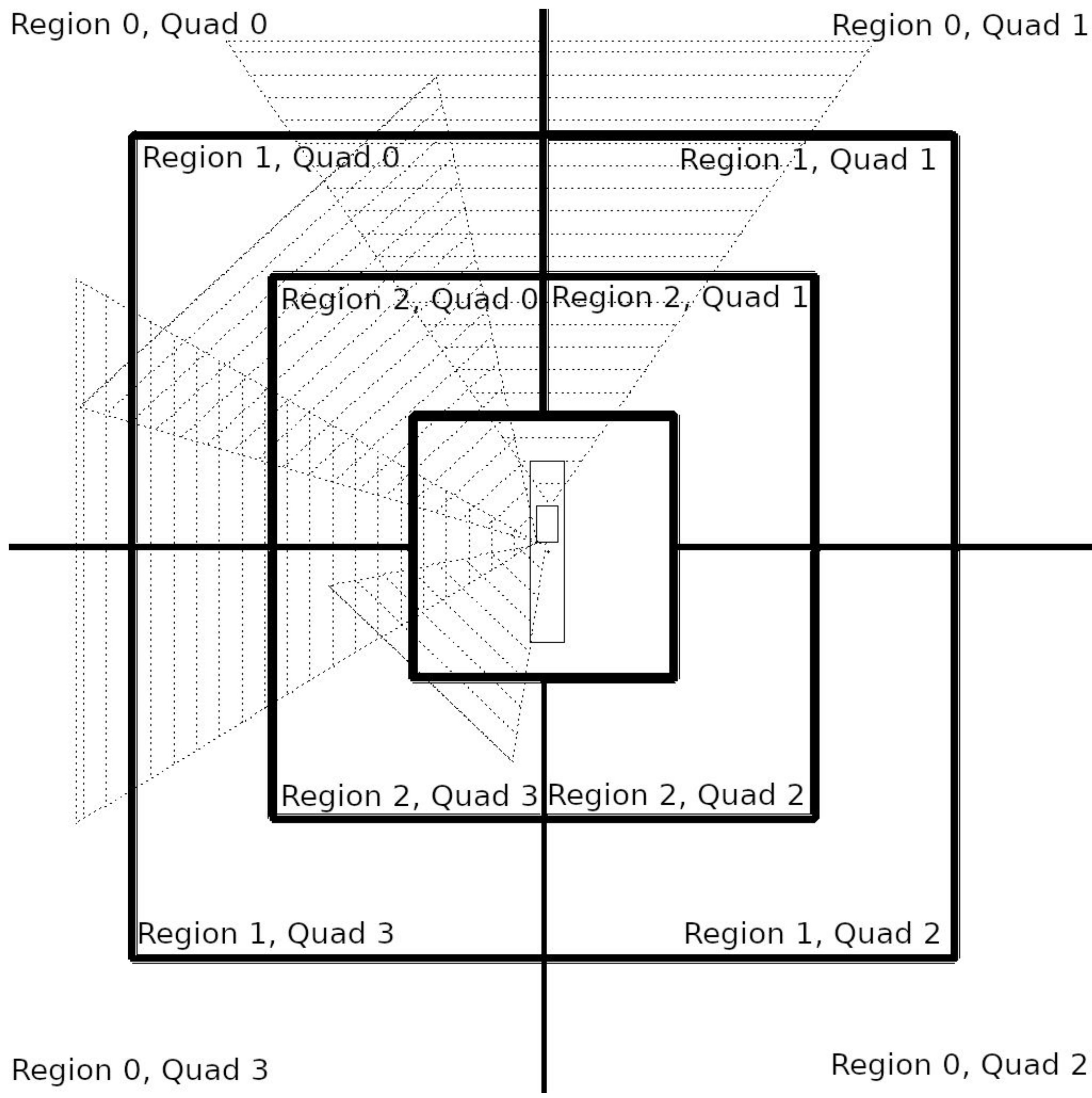
Solution: create a synthetic dataset inspired by IPATCH activity definition and trajectories

- Synthetic examples of each activity type are generated stochastically based on parameters:
  - Number of points is the number of recorded points
  - Sample frequency is the number of pixel level moves on the overhead model between each recorded point
  - Probability distribution is a 9 element vector that represents probability of moving in each direction sorted by how well it will fit the activity being generated (8 adjacent pixels or remain in place)

Approach 1: Computing With Words (CWW)

Computing with words (CWW, HCII 2020) approach assigns regions around an asset ship and trajectories of detected objects are described by a string based on how it moves through these regions.

- Each region is broken into 4 quadrants
- The string is built by iterating over the points and is appended to when it enters a new region or quadrant
- + Fast and does not require training data
- - Least accurate model
- - Does not fit real world data well as quadrants are rigid model



Approach 2: Markov trajectory Feature Classifier (MTFC)

When a new trajectory is observed, we find which model best describes the point-to-point transitions for classification. Each point in a trajectory is described with 4 variables. Accuracy depends on amount of training data. The method is slow and impractical to use in real time

(1) Displacement: $u = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$

(2) Angular velocity: $\mathrm{v} = \frac{1}{t}\sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$

(3) Velocity: $\omega = \frac{1}{t}\tan^{-1}\frac{y_t - y_{t-1}}{x_t - x_{t-1}}$

(4) Angular displacement: $\theta = \tan^{-1}\frac{y_t - y_{t-1}}{x_t - x_{t-1}}$

Approach 3: Naive Bayes Radial Classifier (NBRC)

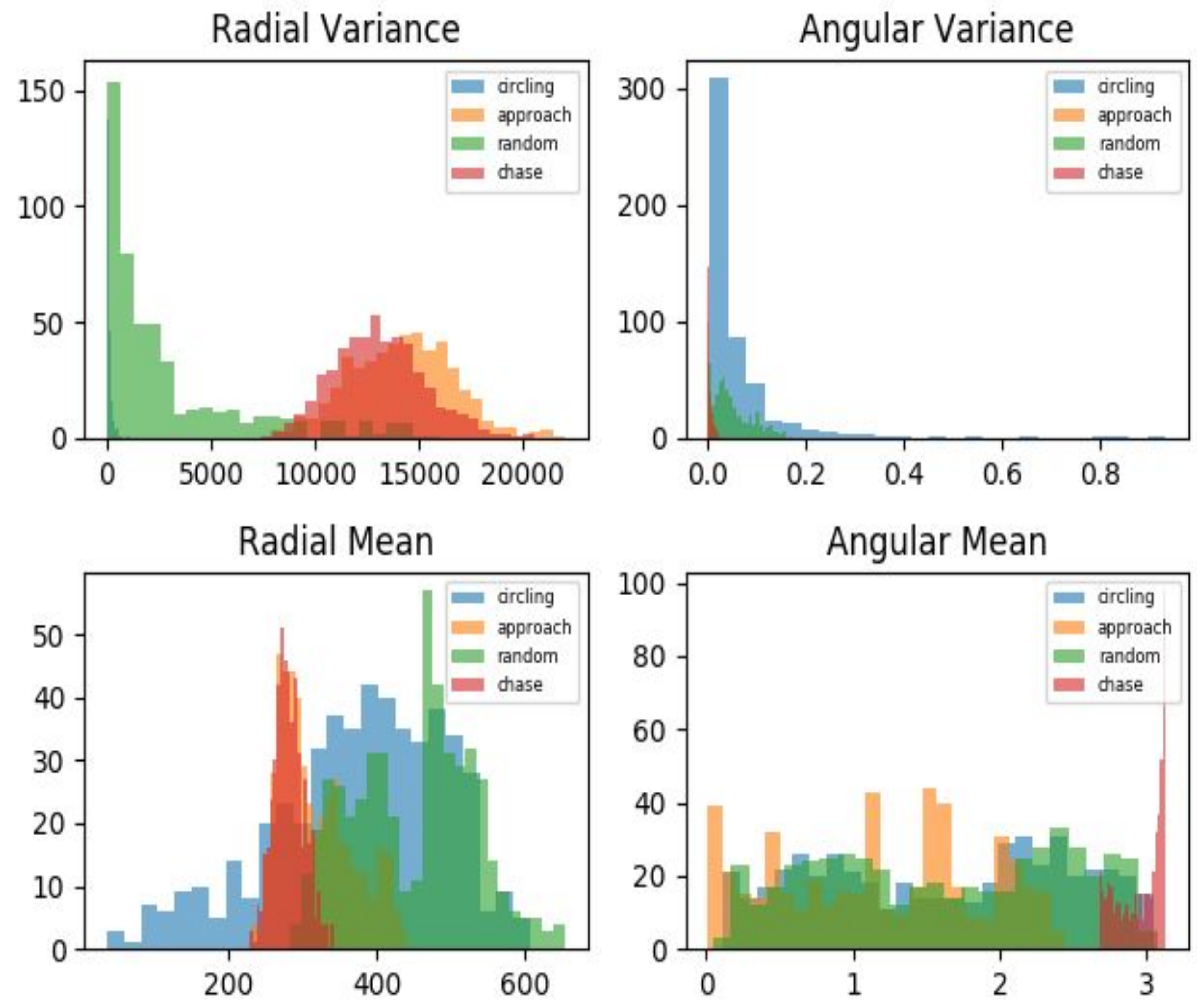
Trajectories are first translated to polar coordinates with respect to the direction the boat is heading

- Theta is calculated as the inverse cosine of the dot product of the normalized vectors representing the ship's bearing and the vector representing the direction from the center of the ship to the detected object. Theta ranges from 0 to pi.
- Trajectories symmetric about the ship's bearing are labeled the same.
- The trajectory is then represented by 4 parameters: radial variance, radial mean, angular variance and angular mean

NBRC: Naive Bayes Radial Classifier

These features give us the most important information about the general shape of the trajectory and roughly follow a normal distribution over our training samples.

- Radial and angular mean tell us generally where on the overhead model our trajectory is
- Radial and angular variance tells us how much each of those variables changes over the course of the trajectory.



NBRC: Naive Bayes Radial Classifier

For each feature of each class, we create Gaussian PDF based on the mean (μ) and standard deviation (σ) from our training data

$$f_c(x_i) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_i-\mu}{\sigma}\right)^2}$$

The value of this function at any point is a likelihood that value would appear given the known mean and variance of the training data

$$L_c = \prod_i f_c(x_i)$$

Experiments

Synthetic dataset is generated for baseline activity (random trajectory) and 3 other activities:

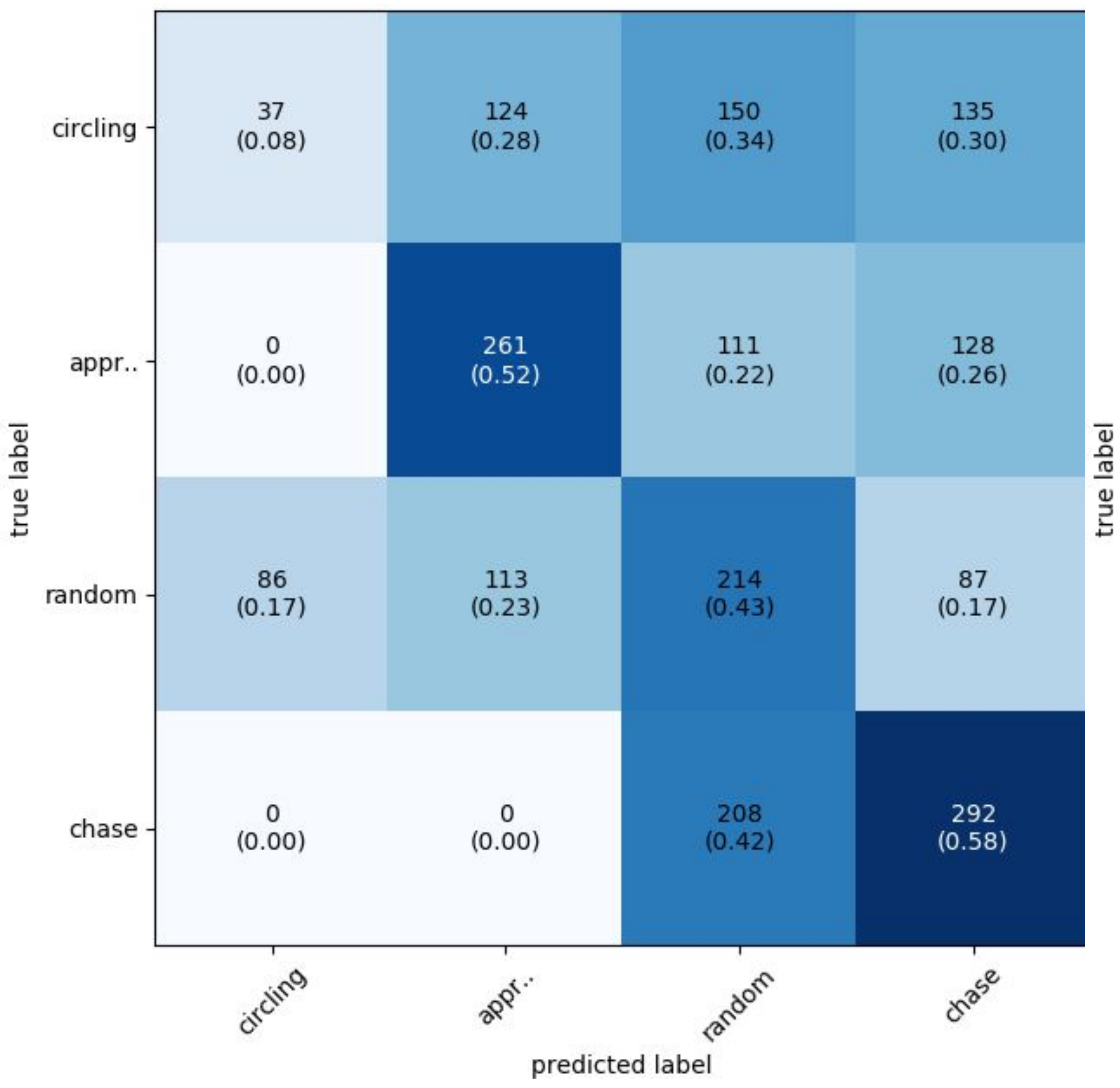
- boat chasing other boat
- boat approaching the ship
- boat circling the ship

CWW does not need training data and is used as a baseline approach.

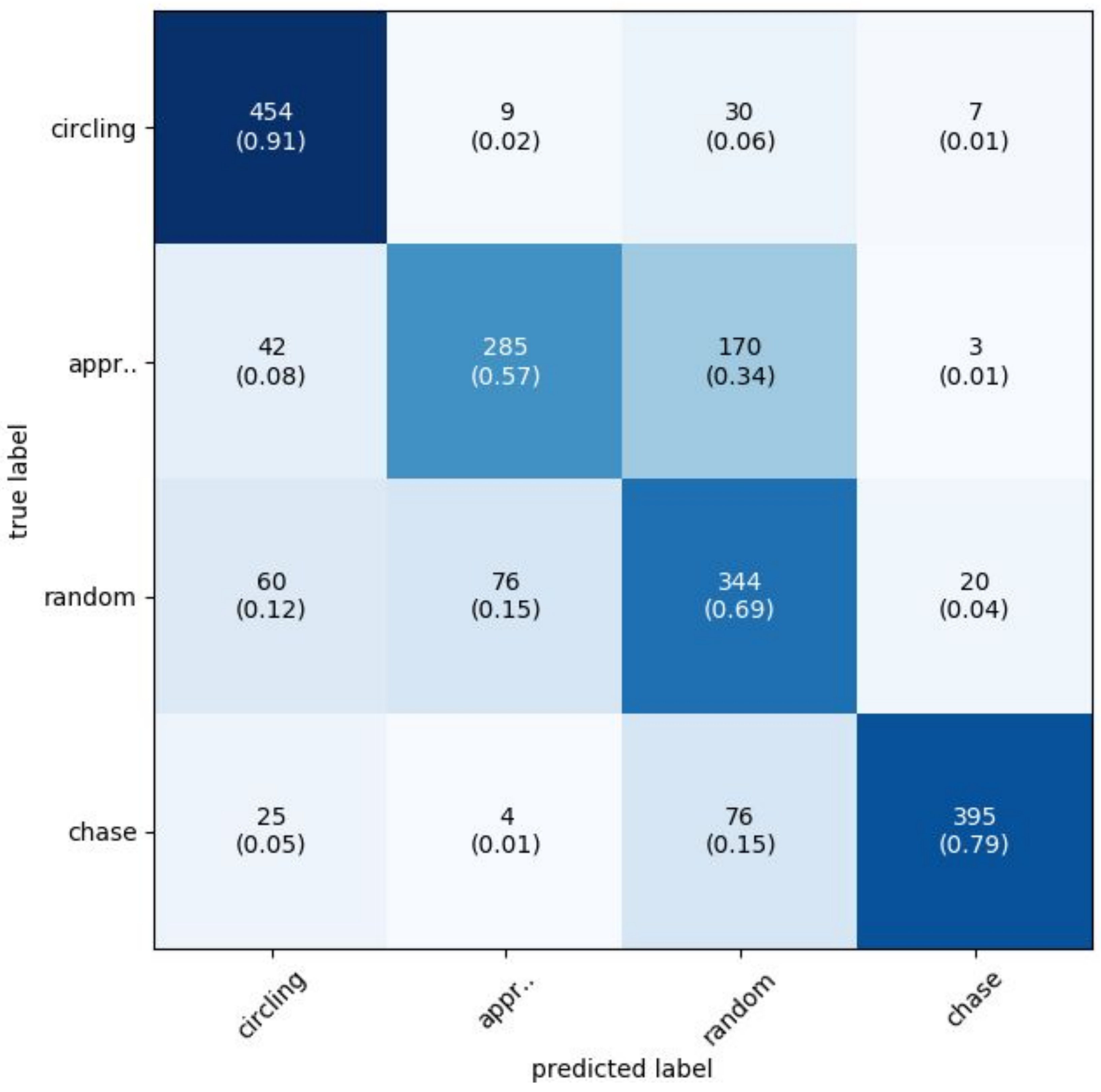
- Training set of 500 generated trajectories is used to estimate parameters in NBRC and MTFC approaches.
- Test data consists of 500 generated trajectories

Confusion Matrices on Test Data

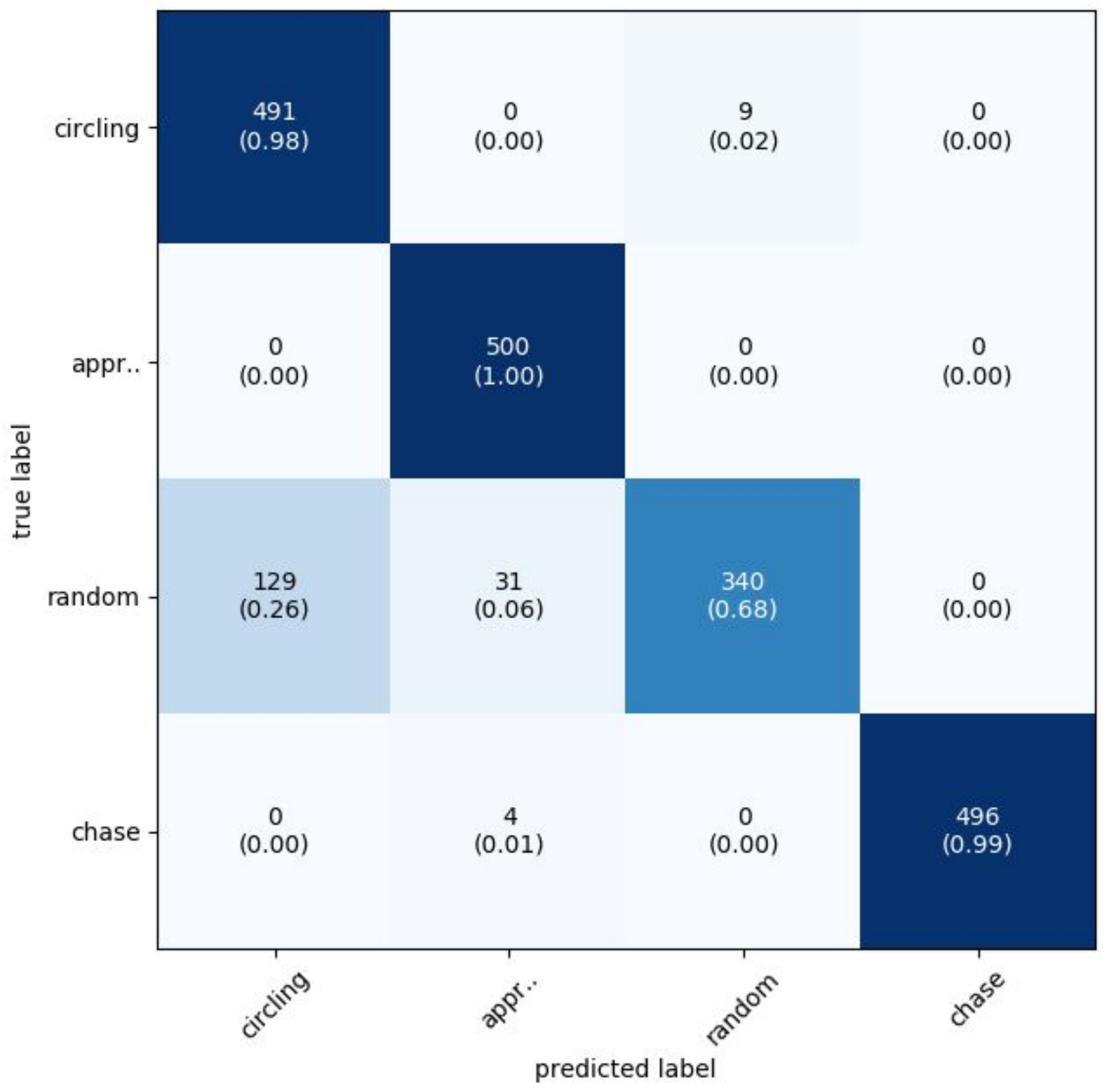
CWW



MTFC

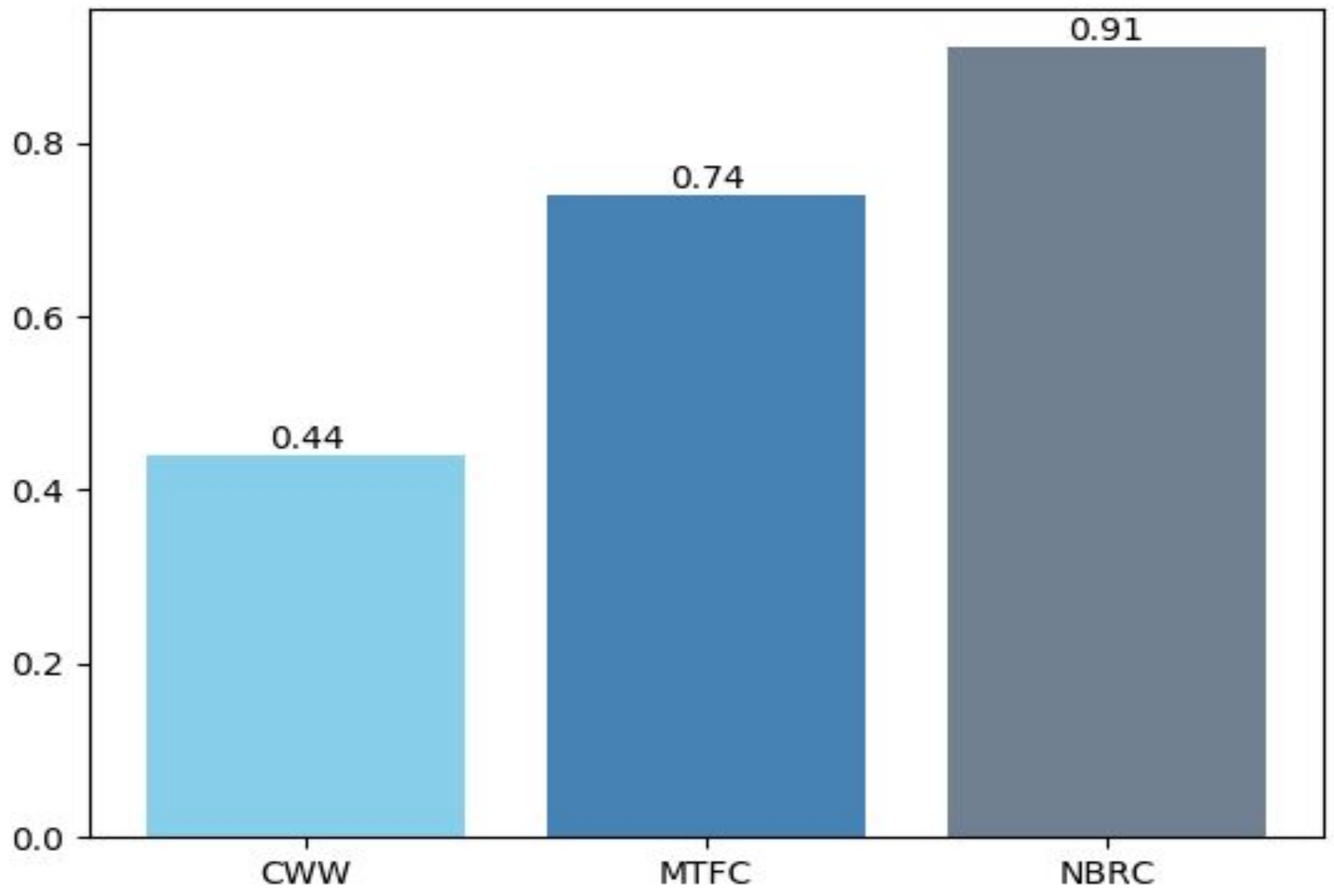


NBRC



Conclusion And Future Work

- Gaussian Naïve Bayes classifier over the radial trajectory features showed far better results than feature-based modeling or region based CWW with 91\% accuracy on test data.
- Radial-based modeling in overhead plane leads to robust scores in multi-camera setting.
- Future Work:
  - Find more real scenarios and validate the findings.
  - Expand and formalize contextual threat analysis



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- Alan Turner implemented the first version of multi-camera tracking and overhead projection
- Sebastian Santana trained and evaluated more efficient object detection and tracking models, and labeled vessel activities.

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Thank you!

DataLab12.github.io for project details and code release

REFERENCES

- IPATCH project: http://www.ipatchproject.eu/
- M. Andersson *et al*., "The IPATCH System for Maritime Surveillance and Piracy Threat Classification," *2016 European Intelligence and Security Informatics Conference (EISIC)*, 2016, pp. 200-200, doi: 10.1109/EISIC.2016.054.
- N Warren, B Garrard, E Staudt, J Tesic, Transfer learning of deep neural networks for visual collaborative maritime asset identification, 2018 IEEE CIC.
- DB Heyse, N Warren, J Tešić, “Identifying maritime vessels at multiple levels of descriptions using deep features”, Artificial Intelligence and Machine Learning for Multi-Domain Operations SPIE 2019.
- J Tešić, D Tamir, S Neumann, N Rishe, A Kandel, Computing with Words in Maritime Piracy and Attack Detection Systems, International Conference on Human-Computer Interaction, 434-444.