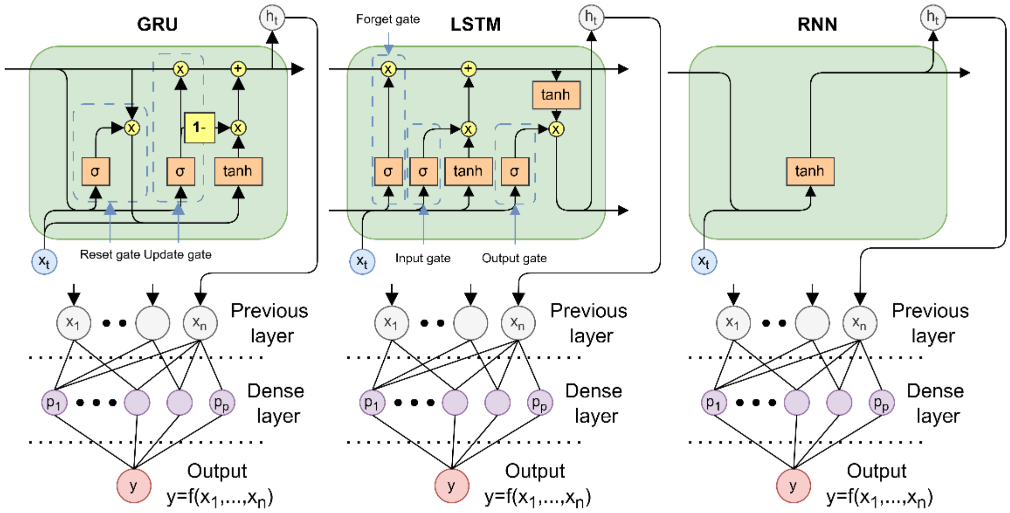
Experiments and actions on the pilot projects 3 until 31.12.2024

Personal Watercraft Trajectory Prediction and Classification



CHALLENGE! To build a model for the automatic detection of potentially reckless and inexperienced personal watercraft drivers, monitor rental boats, and predict the driving behavior of motorboat operators.

HOW? Detecting trajectory anomalies using inflection point sequences, and using a Bayesian, Markov chain, and different machine learning models for forecasting.

WHY? To provide the necessary information to avoid collisions and hazards, especially in crowded spaces during the peak of the tourist season in crowded or narrow areas.

FINAL RESULT→ Anomaly detection, and forecasting models for small personal vessels.

GOALS FOR INNO2MARE PROJECT: To assist in creating a new speed-limiting algorithm for small personal watercraft operators that could replace the existing proximity-based approach.

Progress

Experiments and actions on the pilot project so far:

1. Using inflection points for similar trajectory retrieval

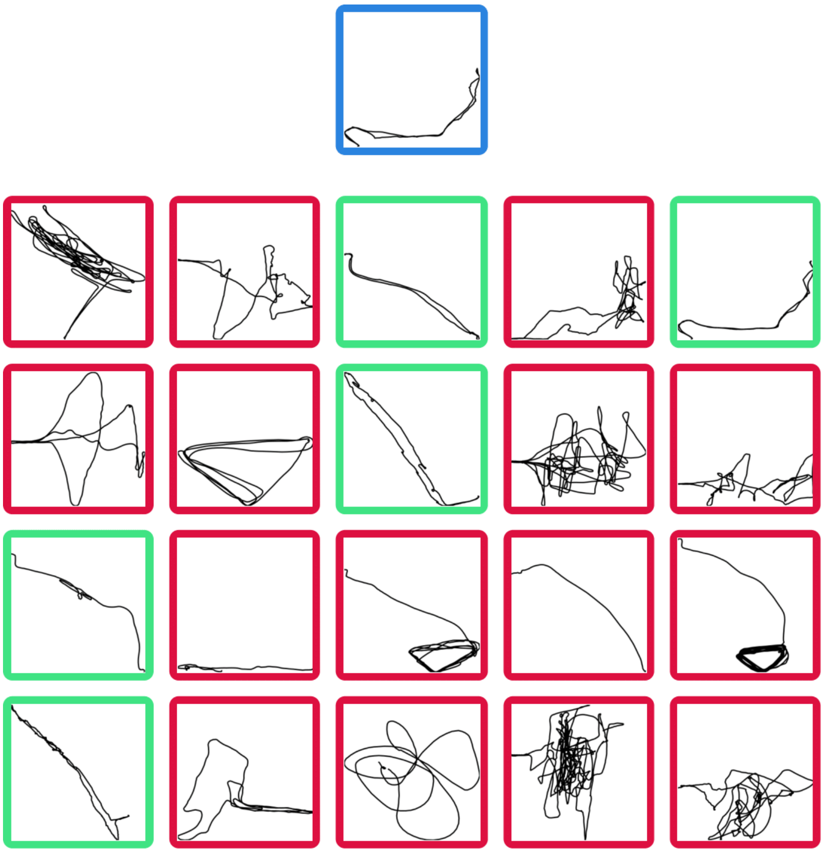
The key purposes of our pilot project include similarity metric design, trajectory classification, and clustering, and the modification of machine learning approaches for forecasting that will enable the development of a novel approach to ensure the safety of all maritime traffic participants by aiding the navigation decision process for vehicles that are semi-autonomous, and optionally remotely controlled.

The project focuses on two specific trajectory-related tasks:

– the identification of similar drivers by examining trajectory patterns.

– the long-term and short-term prediction of watercraft trajectories.

Gathering real-world training data was essential for all the described models. However, we also filtered the data to enhance the quality of trajectories, thus avoiding interpolation that could be misleading, especially in cases where large gaps in transmission were observed.



Below are the key activities implemented thus far in assembling an anomaly detection model:

- **Data Collection and Analysis**: We merged data for 2171 rides from 14 locations, and 19 vehicles in Croatia, Spain, Portugal, Greece, Canada, and the United States of America recorded in July 2022, and 2023.
- **Conducting a Human Similar Trajectory Selection Experiment**: Experts manually selected 5 out of the 20 trajectories in a web interface based on the perceived similarity to a baseline trajectory.
- **Anomaly Detection**: We used DBSCAN and k-Means clustering to divide trajectories into anomalous and non-anomalous based on their similarity generated using inflection point sequences.

Transmitted longitude, latitude, speed, and timestamp data from different locations was essential for training a model that can be applied to new data after preprocessing without additional training. Expert feedback was compared to algorithm selection, and clustering to validate the generated classification. Clustering algorithms provided a basis for comparison with user selection.

2. Developing a Bayesian and Markov chain approach to short-term and long-term personal watercraft trajectory forecasting

We developed Bayesian, and Markov chain approaches to long-, and short-term trajectory forecasting without machine learning using several approaches:

1. A Bayesian, and Markov chain approach using one or two previous states;
2. A Bayesian, and Markov chain approach using one or two previous states, and conditional probability dependent on wave height;
3. A Bayesian, and Markov chain approach using one or two previous states, and conditional probability dependent on wind speed;
4. A Bayesian, and Markov chain approach using one or two previous states, and conditional probability dependent on temperature.

We tested additional meteorological, and environmental variables, such as wave height, wind speed, and temperature, to examine their impact on small maritime vessels. It was confirmed that personal watercraft trajectories are not significantly affected by these external conditions, since their operation inherently creates large waves, and tourists usually avoid extreme weather. An additional previous state reduced the forecasting errors. Performance was not satisfactory compared to competing models, especially for longer forecasting times, motivating the development of machine learning methods.

3. Developing a neural network for personal watercraft trajectory forecasting

Building upon the SeaStateSynth pipeline, we included 5 additional modules to synthesize richly annotated images containing small objects in the sea:

1. Recurrent neural network (RNN) models with simple RNN, long short-term memory (LSTM), or gated recurrent unit (GRU) layers in four architectures - forecasting the trajectories of automobiles on highways;
2. A GRU attention model architecture with four experiment settings - used for sequence-to-sequence translation, adapted to process numbers;
3. LSTM bidirectional and convolutional models for peptide self-assembly - adapted for prediction instead of classification, processing trajectories instead of sequential properties, and aggregation propensity;
4. The **Uni**fied **T**ime Series **M**odel (UniTS) model - developed for use on diverse time-series data, and tasks, without retraining, but adapted to our data using zero-shot.

Different architectures with various hyperparameter settings were examined on the testing data. Similar methods are well established for other vehicles, including land vehicles such as automobiles and larger maritime vessels that follow predetermined routes. We evaluated the models based on root mean square error (RMSE), to enable comparison with relevant literature sources that inspired their development. Execution time was monitored to determine the practical utility in real-world maritime environments. We identified the UniTS model as the best-performing model. We are presently adapting the established method to produce a model that can be embedded on a personal watercraft.