Exploring Large-scale Trajectory Data through 2D Time-space View

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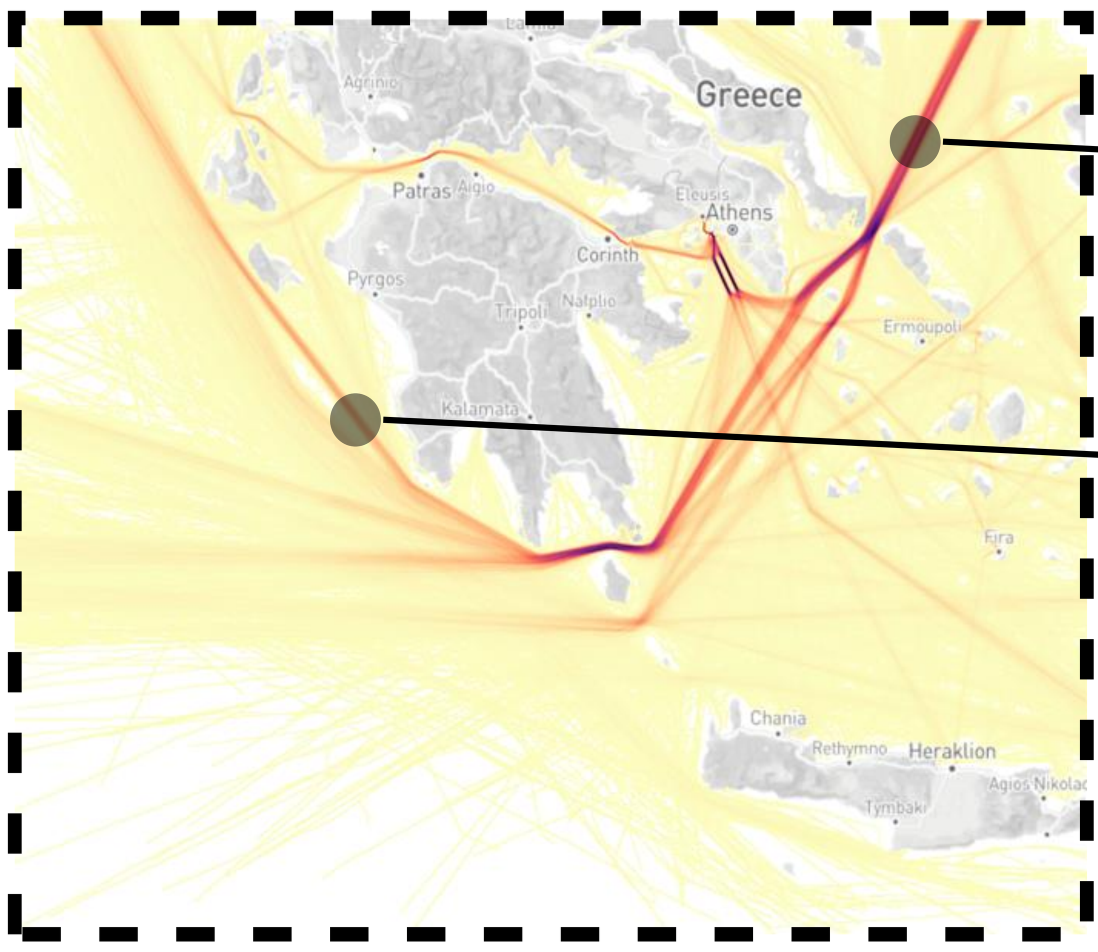
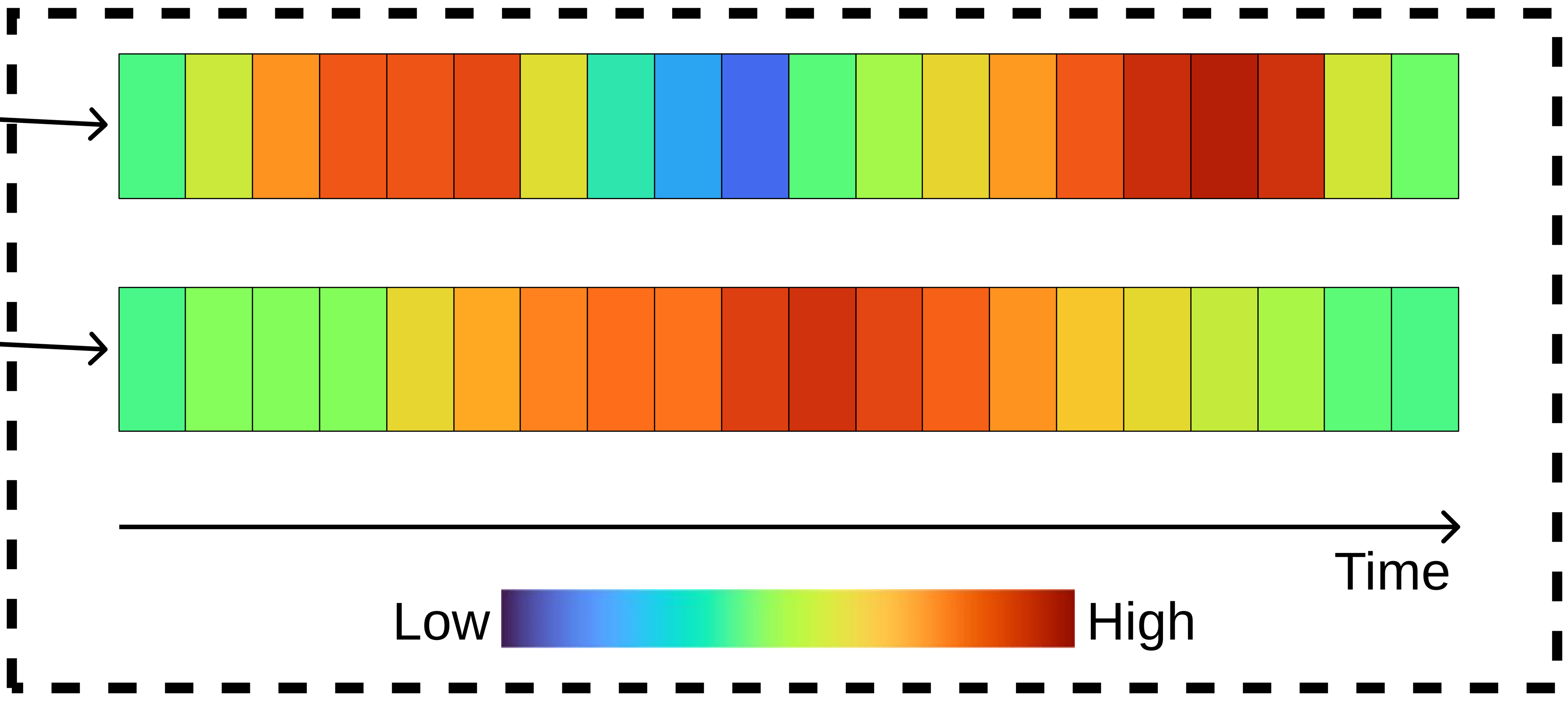




A Spatial view with a line-based density plot to display spatial patterns and brushing for selecting regions of interest (ROI)

B Temporal view with color encoding to represent temporal-related attributes (such as speed or number of trajectories) of the ROI

Motivation

- **Visualizing Large-scale Trajectory Data**
  - Trajectory visualization attributes include space, time, and other associated properties such as velocity.
  - Visualizing both temporal and spatial information on a 2D view is challenging, as one of the dimensions must be discarded in a single 2D view.
- **Limitation of Space-time Cube**
  - The space-time cube uses the time axis as a third dimension, which presents challenges in user comprehension due to its less intuitive operation and higher learning curve.
  - Furthermore, it causes severe visual clutter when dealing with large-scale data, such as datasets containing tens of thousands of trajectories.
- **2D Time-space Multi-view**
  - 2D views are more intuitive than 3D views and interactions are easier to understand, thus we propose focusing on 2D visualizations that separately handle spatial and temporal features.

Goals

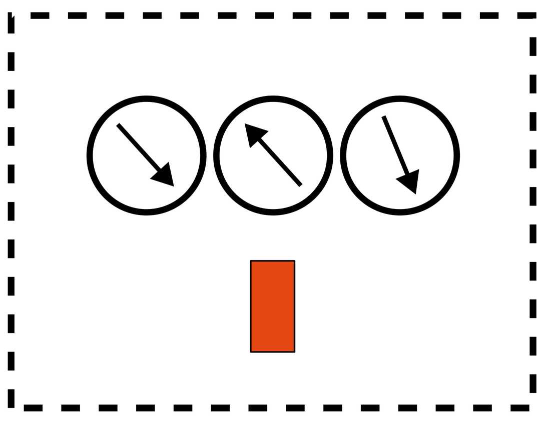
- **Primary Objective**
  - To develop a user-friendly, efficient, and scalable visualization method that leverages 2D multi-view techniques to effectively represent large-scale spatio-temporal trajectory data.
- **Sub-goals**
  - **Enhance Usability**: Focus on creating an intuitive interface that allows users to easily interact with and explore large datasets.
  - **Improve Interaction**: Provide tools that enable users to select regions of interest, query data, and filter results with minimal effort.
  - **Optimize for Scale**: Ensure that the visualization method can handle large datasets without significant performance degradation, allowing users to focus on aggregated patterns rather than individual trajectories.

Limitations

- **Fixed Time Slices**
  - The use of fixed-length time slices limits flexibility in time range selection.
- **Directional Control**
  - While clustering supports direction filtering, some users prefer manual direction selection.
- **Precision Loss**
  - The binning approach sacrifices some precision and user freedom, particularly in large-scale data handling.
  - Color-coding temporal attributes may hinder users from detecting small differences.

Method

1. **Binning**
   - Data Aggregation: We aggregate the spatio-temporal data into a 3D bin matrix, capturing x, y, and time dimensions.
   - Data Structure: Each bin records trajectory IDs passing through it, enabling both spatial and temporal visualizations.
2. **Spatial View and Region of Interest Selection** A
   - Line-based Density Plot: Density in the spatial view is calculated by combining bins across time slices, showing overall spatial distribution.
   - Interactive Region Selection: Users can select regions of interest (ROI) in the spatial view, which are then expanded along the time axis for detailed temporal analysis.
   - Data Projection: ROI selection aligns with the 3D bin matrix, ensuring consistency across spatial and temporal views.
3. **Temporal View and Interactions** B
   - Time Band Analysis: Each ROI in the spatial view corresponds to a time band in the temporal view, divided into intervals matching temporal bins.
   - Visual Encodings and Interactions:
     - Time Band Coloring: Time bands are color-coded based on user-selected attributes (e.g., velocity, density) with options for aggregated statistics.
     - Direction Filtering: Users can filter trajectories by direction in the temporal view, with clusters displayed for easy selection.



     - Temporal Correlation Across ROIs: Temporal correlations between ROIs are explored by intersecting trajectory sets, with color-coded similar time slices.