STAR: Spatio-Temporal Trajectory Recovery for Sparse and Uncertain Marine Trajectories

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Abstract. Mining marine trajectory data has broad applications, e.g., offering valuable insights for individual navigation. Existing trajectory recovery algorithms often overlook the hidden features behind uncertain marine trajectories. This limitation hampers the accurate recovery of trajectories under low sampling rates. In this study, we introduce STAR, a **S**patio-**T**emporal tr**A**jectory **R**ecovery system designed to recover real trajectories with limited information. STAR employs an integrated encoding module to capture correlations among temporal, spatial, directional, and velocity features, uncovering latent patterns in uncertain trajectory data. The system compares predicted trajectories against actual trajectories, providing a visual representation of recovering performance. Experimental results demonstrate that STAR improves the root mean square error (RMSE) by 3.74% compared to state-of-the-art methods, highlighting its effectiveness in trajectory recovery. The demonstration video is available at https://github.com/linng12145/STAR.

Keywords: Spatio-temporal trajectory recovery · Uncertain marine trajectories.

1 Introduction

Advancements in Internet of Things (IoT) technology, sensing systems, and satellite positioning generate vast trajectory data in marine transportation, offering significant value across various domains. However, the rapid increase in traffic data volume poses challenges for existing research and technical solutions, which struggle to deliver high-quality responses when processing large-scale traffic data. Consequently, developing efficient trajectory recovery methods to enhance low-quality trajectory data has become crucial.

Several methods have been proposed to address this problem. Xia et al. [2] introduced AttnMove, an attentional neural network designed to densify individual trajectories by reconstructing unobserved locations with high spatio-temporal accuracy. Zhang et al. [3] presented TrajBERT, a novel approach employing deep bi-directional representations of vessel movement patterns to predict final destinations. While these studies have significantly advanced trajectory-recovery technology, discovering latent feature patterns for more efficient trajectory-recovery remains a critical challenge.

To tackle this problem, our model utilizes a Transformer encoder architecture, which recovers sparse trajectories by analyzing global information. This approach is enhanced by an integrated encoding module, which establishes the correlation of temporal, spatial, directional, and velocity information, facilitating robust trajectory recovery [1].

2 System Overview

The system is comprised of three components: a data preprocessing unit, a trajectory recovery unit, and a visualization unit.

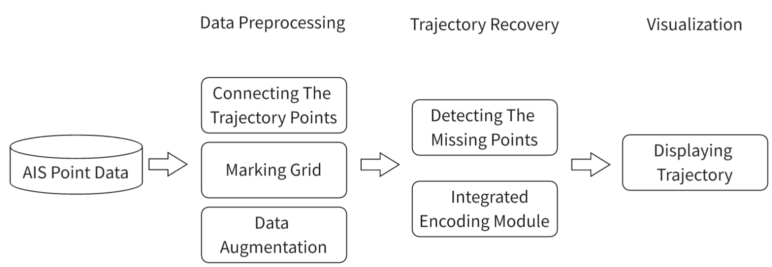


Fig. 1: System framework

Data Preprocessing Unit. In this study, we utilize AIS data by focusing on six key attributes: ship identifier, timestamp, longitude, latitude, velocity, and direction. The preprocessing steps are as follows: First, trajectory points are connected to form continuous trajectories, ensuring that the time intervals between adjacent points within a trajectory are not excessively large. Secondly, each point is assigned a grid number, and grids with fewer than 10 visits are excluded to reduce noise. Finally, a data augmentation strategy is employed by randomly deleting multiple consecutive trajectory points from each trajectory to simulate missing data scenarios.

Trajectory Recovery Unit. To recover missing trajectory points, we begin by identifying their positions and the number of points requiring recovery. We then utilize an integrated encoding module to establish correlations among various trajectory features.

A Multilayer Perceptron (MLP) is defined to map the directional and velocity information from a single dimension to a d-dimensional vector as follows:

$$y(x) = \mathbf{W}_2 \left(\mathrm{GELU} \left(\mathbf{W}_1 x + \mathbf{b}_1 \right) \right) + \mathbf{b}_2, \tag{1}$$

where $\mathbf{W}_1 \in \mathbb{R}^{H_{\dim}}$ and $\mathbf{W}_2 \in \mathbb{R}^{D \times H_{\dim}}$ represent the weight matrices, while $\mathbf{b}_1 \in \mathbb{R}^{H_{\dim}}$ and $\mathbf{b}_2 \in \mathbb{R}^{D}$ are the corresponding bias terms. The activation function $\mathrm{GELU}(\cdot)$ denotes the Gaussian Error Linear Unit.

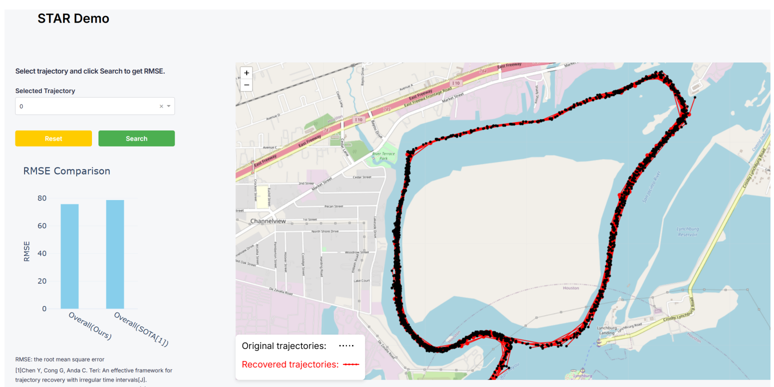
As a result, the hidden feature of the trajectory i can be combined and represented in the following form:

$$\mathbf{x}_i = z(t_i) \| z(c_i) \| y(\theta_i) \| y(v_i) \tag{2}$$

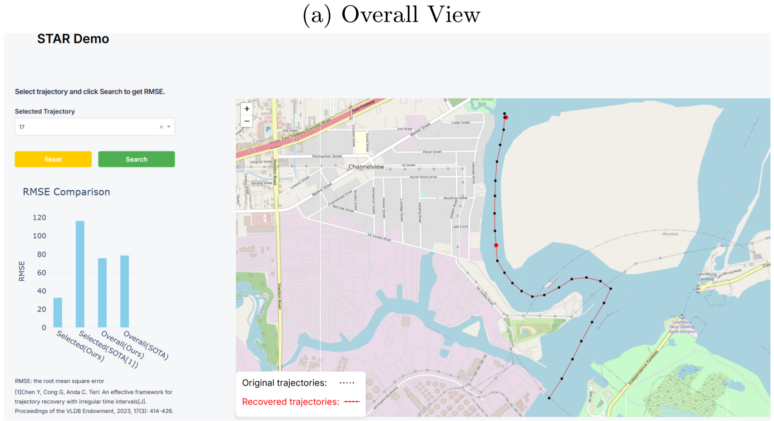
where $\|$ denotes vector concatenation, $z(t_i)$ and $z(c_i)$ represent the temporal and spatial encodings of the timestamp and location coordinates, respectively, as obtained from [1]. On the other hand, $y(\theta_i)$ and $y(v_i)$ denote the encodings of the direction θ_i and velocity v_i, which are computed using Equation 1.

Visualization Unit. The system provides an intuitive visualization by displaying the recovered trajectories alongside their corresponding original trajectories. This feature allows users to directly evaluate the model's recovery performance. This visualization not only aids in qualitative evaluation but also provides insights into potential areas for model improvement.

3 Demonstration



(a) Overall View



(b) One Specific Recovered Trajectory

Fig. 2: Demonstration Functionality

Figure 2a provides a comprehensive illustration of the demonstration system's functionality. In this visualization, users can observe both the **original trajectories** and the **recovered trajectories**. Specific details include:

- **Original Trajectory:** Represented on the map with black points.
- **Recovered Trajectory:** Highlighted the corresponding recovered trajectory points in red.
- **Evaluation Metrics:** The left panel displays the overall Root Mean Squared Error (RMSE) values obtained from evaluating the system's recovery performance using **STAR** and the state-of-the-art (SOTA) approach [1].

Users can select a trajectory via a drop-down menu or by clicking on the map. Figure 2b illustrates a demonstration of a selected trajectory. Once selected, only that path is shown, with RMSE comparisons displayed. Clicking the reset button returns the map to its original view.

4 Conclusion

We developed STAR, a system that leverages AIS data to perform trajectory recovery over sparse and uncertain marine trajectories. It learns hidden features by integrating temporal, spatial, directional, and velocity information. Additionally, it visualizes the recovered trajectories, which enhance marine traffic monitoring capabilities.

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