AISS 23
Autonomous Inland
& Short Sea Shipping

Hybrid Transformer-CNN model with spatial awareness for inland vessel trajectory prediction

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Abstract

Vessel Trajectory Prediction (VTP) is an important aspect in automation of vessel guidance as adequate reactions to critical situations can be planned in advance. Many deep learning-based approaches have recently been proposed. Whereas most of them make use of spatio-temporal vessel dislocation data extracted from Automatic Identification System (AIS) logs, additional data sources such as radar images or Inland Electronic Navigational Chart (IENC) are rarely used [1-9]. Especially in inland navigation where vessels navigate in confined spaces, it is, however, essential to consider information about the navigational environment. Therefore, in this work, an inland VTP model is proposed that makes use of data extracted from IENC and waterway data (flow velocity, flow direction and water depth) alongside AIS data. A Transformer and a Convolutional Neural Network (CNN) are combined in a hybrid deep learning architecture. The model processes information of the past two minutes of a vessel's trajectory and predicts the upcoming minute. Spatio-temporal data obtained from AIS are interpolated to obtain regularly sampled time series with a time step size of 15 seconds. This is close to the average AIS messaging frequency of 10 seconds. The data extracted from IENC, and the waterway data are rasterized. The obtained rasters for an area around a vessel location are rotated into the direction of navigation of the vessel. For each vessel position in the input time series, such rasters are generated. A CNN auto-encoder is trained beforehand on this raster data. The latent representations produced by the pre-trained CNN encoder from rasters is then passed, together with the change in course over ground (COG) changes and Euclidean distances between subsequent time steps, to the Transformer. The prediction results are evaluated using Absolute Trajectory Error (ATE) metric as proposed in [2]. They show that the proposed hybrid approach produces more accurate and realistic predictions compared to a model solely relying on data from AIS.

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