Towards a Unified Vessel Traffic Flow Forecasting Framework

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Abstract
Vessel Traffic Flow Forecasting (VTFF) is vital for maritime harbor supervision, safety management and collision avoidance. Previous works approach the VTFF problem from two different perspectives: a) directly - by predicting the future traffic based on sequence analysis of historical traffic flow,and b) indirectly - by estimating the future traffic based on future vessel locations produced by vessel route forecasting algorithms. In this work, we introduce the Unified Approach for VTFF (UA-VTFF) method by taking advantage of both the indirect and direct paradigms. Our method, in order to predict the future vessel traffic flow in a time horizon of up to 30 min for a specific space, utilizes the results of the indirect paradigm by feeding them into a model that approaches the VTFF problem directly. UA-VTFF is validated over real Automatic Identification System (AIS) data and compared to baseline methods with quite promising results.

Keywords
Machine Learning, Maritime data, Neural Networks, Vessel Route Forecasting, Vessel Traffic Flow Forecasting

1. Introduction

In the maritime domain, it is vital to ensure safe and efficient sailing as the traffic on the waterways increases [1]. Vessel Traffic Flow Forecasting (VTFF) is important in the maritime field. For instance, forecasting vessel flows is crucial for the maritime industry to plan fleet routes and for maritime authorities to manage safety and assist effective collision avoidance.

Maritime traffic information systems can monitor vessel traffic in sea waters. Although such commercial systems often provide proactive traffic management, their forecasting capability is based mainly on linear prediction methods [2], controlled mostly by domain experts. Also, on the one hand, linear prediction methods are fast and robust when vessels stably sail in straight track, but on the other hand, they are unreliable, as they lack the desired accuracy when vessels are in a maneuvering phase (changes on their course and/or speed) [2].

Over the last decade, Machine Learning (ML) based techniques have attracted research interest to develop traffic-related models for the maritime industry as ML methods are very effective in modeling nonlinear plants [3][4]. An advanced monitoring system is presented in [5, 6]. Monitoring and analysing vessel traffic assists in understanding vessels' navigation patterns [7] and, as a result, managing maritime traffic [8]. In order to improve maritime traffic management and, at the same time, collision avoidance, future vessel traffic flow prediction methods were introduced [9].

In the literature, the most promising methods used in predicting vessel traffic flow mainly employ grid-based representation analysis [10], which approach the VTFF problem from two different perspectives [11]: a) indirect - as a Vessel Route Forecasting (VRF) application via employing predicted vessels locations in the future, and b) direct - as a flow sequence forecasting problem. In [11] a comparative analysis between the indirect and direct cases was presented, and both strategies efficiently forecasted the traffic flow in the maritime area in a short time horizon (up to $\Delta t = 15$min.) and a spatial granularity ranging from 5km to 15km. However, in order to assist effective management of sea safety and collision avoidance [12], a longer prediction time horizon in finer granularity is necessary.

In the indirect VTFF case, it is obvious that the method's performance depends on the prediction performance of the underlying VRF method. The underlying VRF method that was used in [11] was presented in [13], which operates as a multipoint location forecasting model. As a result, in order to predict r future points, the time needed for VRF model execution is multiplied by r. However, for collision avoidance purposes, fast execution times are necessary. Hence, in order to increase the prediction time horizon and decrease the execution times, a novel VRF method is introduced in this work, which is

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able to predict r future points in a single execution.

In the direct VTFF case, the method's performance depends on the feature vector included in the sequential forecasting model. The ML algorithms that were implemented in [11] focused on the traffic of each spatial grid cell on previous timestamps disregarding the traffic that occurs in neighbor-surrounding grid cells on previous timestamps. Hence, in this work we enhance the feature vector by adding new features, such as characteristics derived from neighbor-surrounding grid cells and the time characteristics of traffic flow.

More importantly, UA-VTFF unifies the direct and indirect VTFF cases by utilizing the results of the proposed VRF method within the abovementioned feature vector analysis, i.e. this feature vector analysis is applied to the available historical vessel flows and at the same time to the future vessel locations produced by the proposed VRF method. The traffic flows resulting by the proposed feature vector analysis are being fed to an ML method, which is being trained appropriately in order to predict the future vessel traffic flow up to 30 min. We experiment with different ML methods, such as XgBoost [14][15], Autoregressive Integrated Moving Average (ARIMA) models [16][17], Facebook Prophet [18], and Neural Networks (NNs) [19] (static [20] and dynamic [13]).

In summary, this work builds upon our previous work presented in [11] and substantially improves it in terms of accuracy on smaller sea areas and prediction horizon (from 15 min. to 30 min.).

The rest of this paper is organized as follows: Section 2 discusses related work; Section 3 provides background and preliminary terms; Section 4 presents the proposed unified VTFF methodology; Section 5 describes the available AIS data, presents the experimental setup, and discusses the results of our experimental study; Section 6 concludes the paper and discusses future extensions.

2. Related Work

Research on ML models has created impressive achievements in the past few years [21]. A number of studies covering VTFF problem have been published in the relevant literature. We briefly present the relevant works during the last two years, while an overview of less recent related works can be found in [11].

Li and Ren [22] introduced a multi-step vessel traffic flow prediction method based on a Long Short-Term Memory Encoder-Decoder architecture. Also, they proposed a statistical approach of vessel traffic flow based on AIS data. This method was tested on traffic flow during April 2019 of the Liuhe Waterway in the Jiangsu section of the Yangtze River; this area is about 9km x 11km.

Gargari et.al. [23] presented an approach for long-term traffic forecasting on a container port based on learning similar traffic patterns as a reference for estimating future traffic. They employed seasonal autoregressive integrated moving average (SARIMA) and NN models to predict long-term container vessel traffic at the whole area of the Rajaee port in Iran. The experimental results showed that the NN outperforms the SARIMA models.

In [24] a combined prediction framework based on wavelet decomposition and deep NNs was introduced for predicting vessel traffic flow with time frame interval equal to three hours. The method was applied to traffic flow data derived during July 2017 from the Caofeidian Port bounded by parallels 38.76°N and 39.21°N, and by meridians 118.16°W and 118.79°W; i.e. the tested area was about 50km x 55km.

Wang et al. [25] presented the DWT-Prophet, a hybrid prediction model for vessel traffic flow that combines the discrete wavelet decomposition and the Prophet framework; data were decomposed into an approximate component and several high-frequency components by wavelet decomposition, and then the Prophet framework was trained to predict every component. This method was tested on vessel traffic flow data during January 2018 of the whole area of Wuhan Port Yangtze River Bridge.

In [26] a multimodal learning method named Prophet-and-GRU was proposed for vessel traffic prediction, which focuses on predictions with time interval within an hour. This method is based on a Prophet model to decompose traffic flow sequence into components of different periods and on Gated Recurrent Units (GRU) to make accurate forecasts. For evaluation purposes, a dataset was employed that includes vessel traffic every 30 min in Xiazhimen channel, Ningbo-Zhoushan Port during March 2020. Also, the observation rectangle is of length and width equal to 3.19 and 1.04 nautical miles, respectively.

Rong et al. [27] presented an approach for forecasting long-term maritime traffic that takes into account vessel destination prediction (by using a Multinomial Logistic Regression model) and trajectory prediction (by using Gaussian Process) within a certain route. The aggregation of all ships' positions predictions results in a probabilistic picture of the future maritime traffic characteristics and hotspot areas. The method was tested on an area near the coast of Portugal (bounded by parallels 36°N and 42°N, and by meridians 7°W and 11°W), which was divided into four traffic-groups. According to the authors their model cannot be used for collision avoidance.

In [28], Xu and Zhang proposed a method for forecasting traffic volume in wind farm locations based on Pearson's Correlation Coefficient (PCC) and on GRU model. The GRU model takes as input the spatial impacts of vessel traffic flow on different routes. To verify model's effectiveness and feasibility, the wind farm water area in Jiangsu Province was selected, where 11 observation sections were chosen; if a ship passes through the observation section, the traffic volume increases by 1.

Based on the literature review in [11] and the above-mentioned research works, we can conclude that valuable knowledge from vessels' behaviour can be extracted through the analysis of historical data. However, these works focused on specific places of maritime interest and/or quite big areas that cannot assist effective collision avoidance. Also, most of these works are based on specific VTFF strategies (direct or indirect). On the other hand, in our work we propose the UA-VTFF method, which takes advantage both the indirect and direct paradigms and is capable of predicting traffic flow in open sea and at the same time in smaller sea areas.

3. Background and Definitions

In this section, background and preliminary terms are provided. The main definitions employed in this paper are as follows: Consider a maritime dataset D composed of S vessels, where the s-th vessel consists of m_s trajectories and the j-th trajectory is comprised of n_j^s timestamped positions (sampled at asynchronous time intervals) and can be represented as follows:

$$\begin{gathered}\mathbf{P}_j^s = [\mathbf{p}_j^s(1), ..., \mathbf{p}_j^s(n_j^s)] = \\ [[t_j^s(1),\ \mathbf{o}_j^s(1)], ..., [t_j^s(n_j^s),\ \mathbf{o}_j^s(n_j^s)]], \\ s = 1, ..., S, \quad j = 1, ..., m_s\end{gathered} \tag{1}$$

where $\mathbf{p}_j^s$ is a timestamped position, which consists of timestamp t and location $\mathbf{o}(x, y)$ in the Universal Transverse Mercator (UTM) system.

Definition 1. ***Route Forecasting***:

- **Given**:
  - a set of vessel trajectories D,
  - a vessel's trajectory $[\mathbf{p}_j^s(1), \ldots, \mathbf{p}_j^s(k')]$ consisting of k' consecutive points,
  - a time duration (prediction horizon) Δt,
  - a number of transitions r
- **Predict**: each vessel's future trajectory up to Δt, consisting of a total of r transitions with fixed sampling rate (i.e. $t_j^s(k'+1) = t_j^s(k') + \Delta t/r$, $t_j^s(k'+2) = t_j^s(k') + 2 * \Delta t/r$, ..., $t_j^s(k'+r) = t_j^s(k') + \Delta t$):

$$[\mathbf{o}_j^s(k'+1),\ ...,\ \mathbf{o}_j^s(k'+r)] \tag{2}$$

Definition 2. ***Traffic Flow Forecasting***:

- **Given**:
  - a time duration (prediction horizon) Δt,
  - a number of temporal transitions r,
  - a set of vessel trajectories D spanning in Ds (minimum bounding box of locations) in space and D_T in time,
  - a set of future vessel trajectories D_P spanning in Ds and $D_T \cup \Delta t$,
  - a spatiotemporal (i.e., 3D) grid that splits a) Ds into grid cells of resolution $G \times G$, and b) $D_T \cup \Delta t$ into r time frames
- **Predict**: the volume of vessels in each cell of the spatiotemporal grid.

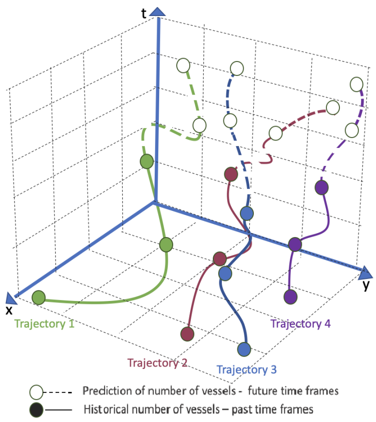


Figure 1: Example of 4 vessel trajectories in a spatiotemporal grid of 5 time frames and 4 × 4 space resolution.

Fig. 1 presents an example of a spatiotemporal grid of 5 time frames and 4 × 4 space resolution. There are 4 trajectories evolving in 3 time frames, and the goal is to forecast the vessels' volume in each grid cell during the 2 time frames in the future.

4. Methodology

In this section, our approach is presented including the enhanced VRF model and the UA-VTFF methodology. An overview of the proposed methodology is illustrated in Fig. 2. More specifically, first, historical AIS data pass through processing operations. Then the VRF method is applied. The processed historical data along with the produced points of the VRF are arranged into a spatiotemporal grid. Subsequently, the resulting traffic flows pass through a feature vector analysis, which are then fed to an ML method for VTFF prediction purposes.

4.1. The enhanced VRF model

In this work, we consider the VRF problem as a direct trajectory forecasting problem. More specifically, in order to train the model, the output data are interpolated on the trajectory's r transitions. Also, the NN consists of $r * 2$ outputs, where for one predicted point, there are necessary two neurons for the two coordinates for space and, as a result, each pair of output neurons gives one

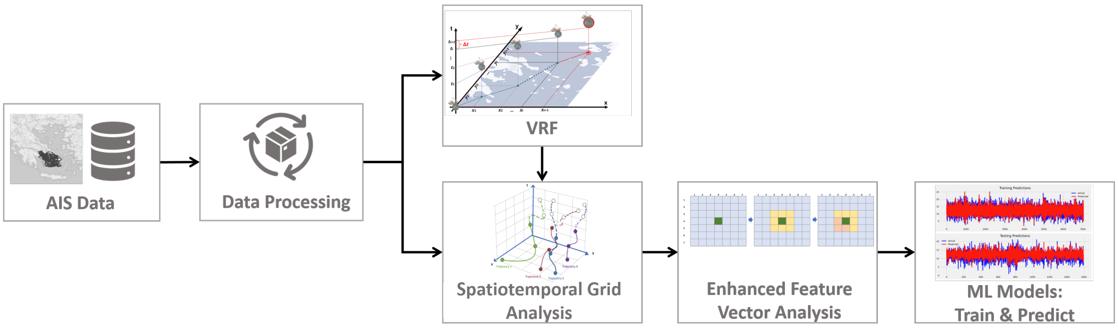


Figure 2: Overview of the UA-VTFF methodology.

forecast for each trajectory's transition. Thus, after the training procedure, we need to execute the NN model only one time in order to produce the desired predictions.

As far as the input information is concerned, three features are given including information regarding the time and the two space coordinates, actually the differences in time and space between consecutive timestamped positions. More specifically, for each timestep $k = 1, \ldots, n_{j-1}$, where n_j is the length of the j-th trajectory, the NN is fed with the input vector:

$$\Delta \mathbf{u}^s_j(k) = \left[\Delta x^s_j(k), \Delta y^s_j(k), \Delta t^s_j(k)\right]. \tag{3}$$

Regarding the NN architecture it consists of an input layer of three neurons, a Long Short-Term Memory (LSTM) [29] hidden layer, a fully-connected hidden layer and an output layer of $r * 2$ neurons. Also, the model parameters can be updated through the Backward Propagation Through Time (BPTT) algorithm [30] and the synaptic weights can be optimized according to the Adam approach [31] in the training set. Overall the NN training phase is followed by a validation phase and, eventually, model selection; the use of a validation set results in measuring the model's generalization ability.

It should be noted that the VRF problem in [11] was considered as a multipoint location forecasting task and the model presented in [13] was employed for predicting the vessel's future locations. This model (after following the training procedure) needs to be executed r times in order to provide predictions for the r transitions forming the future trajectory. On the other hand, our proposed method needs to be executed only one time to produce the desired trajectory and thus the time prediction duration significantly decreases, as it will be shown in the experimental study (in Section 5).

4.2. The Unified Approach for VTFF (UA-VTFF)

UA-VTFF method starts by giving the available vessels' historical trajectories into the proposed VRF algorithm (described in the previous section) in order to predict the future trajectories. Subsequently, the vessels' historical and future trajectories are assigned into the spatiotemporal grid (presented in Section 3) and the calculation of the amount of vessels that are placed in every grid cell is performed. The resulting amounts indicate the volume of the historical vessels n and the predicted vessels η (produced by the proposed VRF model), which represent the traffic sequence in a specific cell-region and time frame. Then, these traffic sequences for every grid cell b are enhanced with additional features, including information regarding timestamp and the volume of vessels in surrounding cells. Finally, the produced sequences are fed to an ML algorithm for predicting the future traffic flow in the grids, i.e. the vessels' amount in a particular cell in future time frame Δt. Fig. 2 presents the above pipeline.

It should be noted that for training purposes the data in the output are also processed as the data in the input. More specifically, in order to predict the vessels' amount in the b-th grid cell in the future time frame $t+1$, i.e., to produce the model output $\hat{n}^{b}_{t+1}$, the corresponding model input N^b_{t+1} for the b-th cell within the grid that comprises l total cells is composed of the following features:

- $n^b_{t-l}, \ldots, n^b_{t-1}, n^b_t$: the vessels' amount n in time frame t in the b-th cell grid
- $n^{b'}_{t-l}, \ldots, n^{b'}_{t-1}, n^{b'}_t$: the vessels' amount n in time frame t in the neighbor-surrounding cell grids b' of b-th cell grid
- $n^{b''}_{t-l}, \ldots, n^{b''}_{t-1}, n^{b''}_t$: the vessels' amount n in time frame t in the neighbor-surrounding cell grids with high traffic b'' of b-th cell grid
- η^b_{t+1}: the vessels' amount produced by the enhanced VRF in the future time frame $t+1$ in the b-th cell grid
- $\eta^{b'}_{t+1}$: the vessels' amount produced by the enhanced VRF in the future time frame $t+1$ in the neighbor-surrounding cell grids b' of b-th cell grid

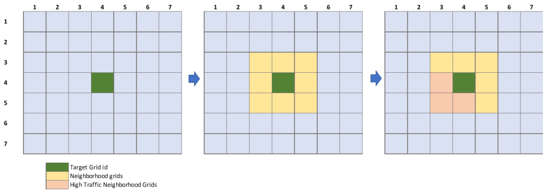


Figure 3: Example of 7×7 neighbor-surrounding traffic cells of a spatial grid.

- $\eta_{t+1}^{b''}$: the vessels' amount produced by the enhanced VRF in the future time frame $t+1$ in the neighbor-surrounding cell grids with high traffic b'' of b-th cell grid
- $md_{t-l}^{b}, ..., md_{t-1}^{b}, md_{t}^{b}$: the day of the month md in each time frame t in the b-th cell grid
- $dw_{t-l}^{b}, ..., dw_{t-1}^{b}, dw_{t}^{b}$: the day of week dw in each time frame t in the b-th cell grid
- $td_{t-l}^{b}, ..., td_{t-1}^{b}, td_{t}^{b}$: the time of day td in each time frame t in the b-th cell grid

Regarding the calculation of the neighbor-surrounding grid cells and those with high traffic, the neighbor cells correspond to those cells that surround the center-targeted. The surrounding grid cells with the highest traffic are those with the highest correlation with the center-targeted and are defined based on statistical analysis and taking into account that these cells should correspond to regions areas associated with a high risk of accidents [32]. To clarify the above discussion, Fig. 3 illustrates a grid with nearby cells only in space of 7×7. The green cell illustrates the central-targeted cell for which a prediction will take place. The yellow cells correspond to the neighborhood cells, while the pink cells present the neighborhood cells with high traffic and high correlation with the center-targeted.

Several ML techniques were used in this study to tackle the VTFF problem. Particularly, we employ XgBoost and ARIMA models, which were trained according to [11]. Also, we employ Facebook Prophet [18], which is a recently presented forecasting technique inspired by the nature of time series predicting at Facebook.

Furthermore, we use static and dynamic NNs. Particularly, for the static NNs, the Multi-Layer Perceptron (MLP) architecture was employed composed of two hidden neurons and trained with the Backpropagation algorithm [19]. Regarding the dynamic NNs, LSTM networks were used composed of an input layer, an LSTM hidden layer, a fully-connected hidden layer and an output layer of two neurons. The LSTM-based architecture was trained following the same procedure as it was described in Section 4.1.

As far as the model parameterization is concerned, various characteristics of every model type were taken into account and adjusted with intermediate observation tests before the final evaluation. In particular, the XgBoost models were optimized regarding the learning rate, the minimum leaf size for pruning, the number of features on a node, and the number of regression trees. Also, the ARIMA model was optimised regarding the lag order, the degree of differencing, and the order of the moving average by evaluating the Partial Autocorrelation plot, the Augmented Dickey Fuller test and the Autocorrelation plots, respectively. Furthermore, the MLP and LSTM NNs were optimised regarding the hidden layers' size, while an early stopping procedure [33] is employed to prevent the networks from overfitting by using a validation set. As far as the Facebook Prophet parameterization is concerned, two parameters were tuned that express Seasonality variance and Trend variance: Seasonality Prior Scale influences the seasonality component of the time series and the values tested ranged from 0.01 (small influence) to 10 (very high influence); Changepoint Prior Scale influences the variance of the trend component and the values tested ranged from 0.05 (underfitting variance) to 0.5 (overfitting variance).

5. Experimental Study

This section presents the experimental setup, along with the results of the tested ML methods.

5.1. Experimental setup

All the methods were implemented using Python and the experiments were conducted in a workstation composed of 64 GB RAM, Intel Core i9-9900KX CPU and GeForce RTX2080Ti GPU.

The proposed method was evaluated on real-world AIS data provided by MarineTraffic.com. More specifically, 1,757,440 AIS records received from 2344 different vessels of various types sailing during November, 2018, in the Aegean Sea rectangle bounded by longitude [23...26] and latitude in [36...38].

As far as the parameters of the VTFF problem formulation are concerned, we used a spatial grid of $G = 2$km, a prediction horizon of $\Delta t = 30$min and a number of temporal transitions of $r = 6$. The produced traffic flow is as follows: A number of 14,340 cells was created, with the traffic flow of min, max, median and mean values equal to 0, 103617, 25, and 120 vessels, respectively. Of the whole grid cells, only 768 cells presented traffic flow of more than 300 vessels across the entire period, while 4,000 cells included less than 10 vessels in the whole period. The top 10 grid cells have more than 5 vessels on average every 5 minutes and include more than 300,000 vessels in the entire period.

It should be noted that we resulted in the abovementioned parameters ($G = 2$km, $\Delta t = 30$min and $r = 6$)

after experimenting with different values of spatial grid's resolution (of G equal to 2km, 5 km and 10 km), number of temporal transitions (of r equal to 3 and 6) and prediction horizon (of Δt equal to 15 min. and 30 min.; based on the tested values of r the overall corresponding time frames were of 5 min. and 10 min.). We observed that the UA-VTFF method is affected by these parameters. More specifically, the model predicts better when the spatial resolution (based on G) is higher and the time frames (based on r in combination with Δt) are bigger, while the impact of the prediction horizon is limited.

Regarding the evaluation of the implemented algorithms, it was performed in the busy grid cells [34], which correspond to regions with regular navigation and heavy traffic, with a high risk of accidents [32]. Areas with low vessel density denote a low level of traffic flow complexity, which implies regular and predictable vessel travel time sequences [35]. This is also confirmed by the experimental study in [11], where the ML model predicts better when there are also non-busy regions; the same ML model was tested on the whole available cells (there were cells with zero traffic) and only on the busy ones.

For all the algorithms, except the indirect VTFF [11], the corresponding traffic flow sequences of the busy grid cells are arranged into input and output data, where for each grid cell, the initial 75% of the traffic flow sequence is used for the training purpose, whereas the remaining 25% of the traffic flow sequence, except for the last six observations (corresponding to 30 min.), is organized in the testing set. Regarding the indirect VTFF, following [11] the trajectories derived from the busy grid cells are then arranged into training, validation, and testing sets of a 50%–25%–25% percent ratio, respectively. Experimental results are evaluated using the Symmetric Mean Absolute Percentage Error (SMAPE) [11].

Table 1
Prediction results (SMAPE) for different alternatives of the UA-VTFF method in the testing set ($G = 2$km)

Method	Time prediction horizon (min)					
	5	10	15	20	25	30
LSTM	12	16	27	26	27	26
MLP	16	21	32	34	37	36
XgBoost	13	19	29	29	29	27
ARIMA	20	24	35	38	47	40
Prophet	21	24	33	33	38	36

Table 2
Prediction results (SMAPE) ($G = 2$km)

Approach	Train set	Test set
UA-VTFF (LSTM)	18	21
UA-VTFF (XgBoost)	19	22
direct VTFF [11]	23	29
indirect VTFF [11]	25	28

5.2. Results and Discussion

Table 1 presents results for the UA-VTFF approach using different ML techniques. More specifically, LSTM, MLP, XgBoost, ARIMA and Prophet are employed. Also, Table 2 presents results for the UA-VTFF approach, the indirect and direct VTFF strategies presented in [11].

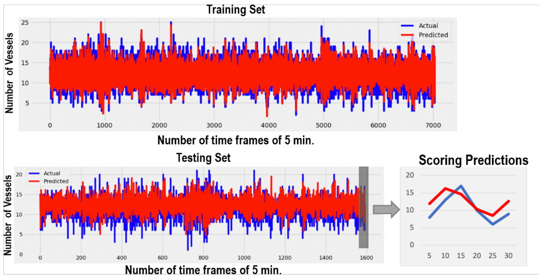
The results presented in Table 1 confirm that the LSTM-based UA-VTFF method can accurately capture the vessel traffic flow in short-term to assist in effective collision avoidance. This is due to the fact that LSTM have emerged as an effective technique for several difficult learning problems [5] and have demonstrated significant performance on predicting sequential problems [36]. Also, our proposed UA-VTFF approach (using LSTM or XgBoost) outperforms the indirect and direct VTFF strategies as summarized in Table 2.

In order to investigate further the performance of the proposed UA-VTFF, we also present results in the two highest traffic grid cells. Particularly, figs 4a and 4b depict the prediction performance of the direct VTFF strategy [11] and the XgBoost-based UA-VTFF algorithm, respectively in the grid cell with id #19837. Also, figs 5a and 5b depict the prediction performance of the direct VTFF strategy [11] and the XgBoost-based UA-VTFF algorithm, respectively in the grid cell with id #19653. More specifically, the figures illustrate the original and predicted traffic flow in the training and testing sets. The figure for the training graphic corresponds to the number of vessels for the first 75% of the 5 min time frames(first 7000 time frames), while the testing graphic corresponds to the number of vessels for the last 25% of the 5 minutes time frames(last 1600 time frames). Finally, we have included the performance of each method on the last six observations of the dataset corresponding to the last 30 minutes. Based on figs 4b, 4a, 5b and 5a we can observe that UA-VTFF has less overfitting in the training data compared to the direct VTFF [11], since in the latter method the training graphic seems to have a much better performance than the testing one. Finally, the XgBoost-based UA-VTFF method performs better in the scoring dataset than the direct VTFF [11], which also uses XgBoost models.

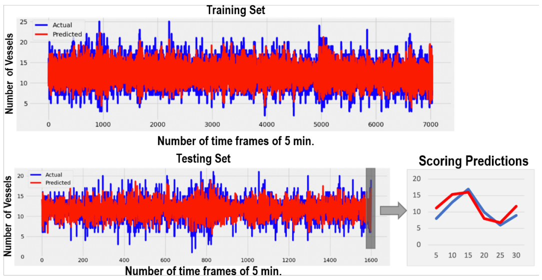
Finally, we should mention that the proposed VRF method manages to predict a vessel trajectory composed of 6 transitions with a latency of about 0.5secs on average. On the other hand, the VRF method used in the indirect VTFF [11] predicts 6 transitions with a latency of about 2.5 secs on average.

6. Conclusion

An effective method for vessel future traffic flow prediction, in terms of accuracy and execution times, can provide the fundamental basis for managing safety and

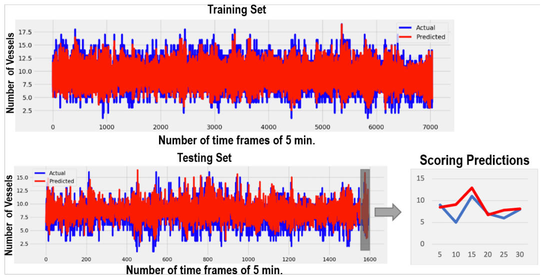


(a)

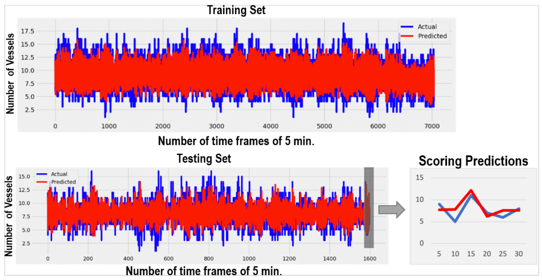


(b)

Figure 4: Prediction performance in training and testing sets for grid cell id 19837 of the: (a) XgBoost-based direct VTFF [11], and (b) XgBoost-based UA-VTFF.



(a)



(b)

Figure 5: Prediction performance in training and testing sets for grid cell id 19653 of the: (a) XgBoost-based direct VTFF [11], and (b) XgBoost-based UA-VTFF.

assisting effective collision avoidance at sea. In order to tackle the VTFF problem, in this paper we build upon previous work, which investigated two different VTFF strategies. Particularly, we take advantage of both the strategies by combining them, we enhance the feature vector analysis, we propose a VRF method that is able to predict the desired vessel trajectory in one execution, and we employ a longer prediction time horizon (up to 30 min.) in finer granularity (of resolution 2km x 2km). Through our experimental study of a real AIS dataset it is obvious that the proposed UA-VTFF method can efficiently forecast the traffic flow in terms of high accuracy. Future work includes the investigation of: a) weather impact on vessel traffic flow, b) tensor factorization analysis, and c) extreme traffic events to fine-tune the model.

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