Probabilistic ship behavior prediction using generic models

Navreet S. Thind[1]; Dirk Söffker[1]

Abstract— **Autonomous systems like inland vessels require knowing the behavior of surrounding vessels and moving objects. Predicting the behavior of surrounding inland vehicles operating in a narrow field like rivers, channels, etc. around the Ego-system is challenging due to the required accuracy. Existing approaches for sea navigation cannot be used because the precision requirements are lower than required for inland vessels navigation. Precise behavior prediction is required that allows navigation with high precision during overtaking in upstream and downstream directions. In this contribution, new approaches have been developed using past trajectories information of different or similar types of inland vessels. Here the concepts of three approaches to predict the behavior, based on AIS data, are discussed and compared. In the first approach, predictions are done with a model developed using simple parameter-based approach. The predictions are based on the global model parameters of the vessel and local adaption. In the second approach, the Bayesian approach is applied to define the best trajectory (intention) from the clustered past information. In the third approach, the two approaches are combined; here, the local parameters from the first model and the intentions from the second model are taken into account so that the prediction errors are reduced. The initial results, from this study, are based on the data of a single ship. A further extension of the approach will consider data from several vessels of the same type.**

I. INTRODUCTION

Ships are the central element of the earth's transportation system, as 2/3 of the earth's surface consists of water. To reduce the transportation cost by reducing the personal and collisions due to human error, autonomous ships are an important research topic nowadays. The topic of autonomous inland vessels is more challenging than sea vessels due to narrow distance required in applications like overtaking other vessels or passing under a bridge. Thus, for safe operations of the vessels, surrounding vessel trajectory prediction is an important task to avoid collisions. As vessels have slow dynamics and cannot stop, turn, or reverse abruptly in high risk areas and situations should be identified as early as possible to apply collision avoidance maneuvers. A suitable strategy is to avoid close-range encounter situations for the vessels [1]. To evaluate trajectory prediction methods, most of the approaches apart from calculating the distance error use the along-track error and cross-track error as shown in Fig. 1. The cross-track error reflects the true movement direction. The along-track error measures the error along the observed trajectory. In this way, it is determined how well the predicted velocity matches the actual velocity of the trajectory. In water transport sector, most of the vessels are required to install AIS receivers to broadcast information like positions, Speed Over Ground (SOG), Course Over Ground (COG), heading, and other information to other vessels and AIS base stations. This information provides an important data information which can be used to predict vessel's behavior using data-driven approaches. The AIS data concept has many limitations like poor data quality, irregular sampling time, environmental factors, as well as different operating situations. In this work an approach is developed to consider different environmental factors.

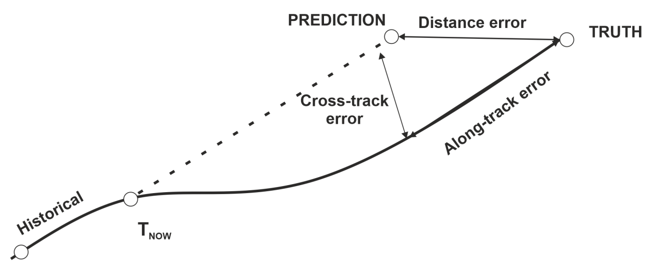

Fig. 1: Prediction error measure [2]

II. RELATED WORKS

In [3] the vessel behavior prediction is characterized into three categories: physical model-based methods, learning model-based methods, and hybrid methods. Physical model-based methods are derived using mathematical equations with linear or kinematic parameters (like mass, inertia, etc.) and physical laws. The Constant Velocity Model (CVM), lateral model, and ship model are examples of physical model-based approaches. In [4] the CVM approach is applied to calculate the closest point of the CPA approach. In [5] the Abkowitz model, developed specifically for ships, is used to predict the maneuvers. The drawback of [4], [5] is that the parameters are assumed constant. Kalman filter (KF) and Extented KF approaches are applied in [6] to estimate ship trajectories to be utilized in collision avoidance. Large number of sensor measurements are required for [6].

Neural networks models are not widely used in vessel trajectory prediction in comparison to vehicles trajectory prediction. Most of the early developed approaches focused on providing traffic information using AIS data. In [7] Gate Recurrent Unit (GRU) model is used to predict the trajectory and is compared with Long Short-Term Memory (LSTM). The errors are in limits of 500 m to 1.5 km and cannot be used in river applications. Online real-time ship behavior is predicted using bidirectional LSTM-RNN based on AIS data. It combines historical experience and real-time data.

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Singe Point Neighbor Search method is used in [8] to predict trajectories for short-term predictions up to 30 minutes. It calculates the nearest point from the historical AIS data, takes all data points into account, and does not cluster trajectories. The authors in [1] expands the approach developed in [8] with clustering and multiple trajectory extraction method and prediction algorithm. In [1] and [8] historical data is considered as points so only current state is compared with the nearest point only. Normally, current states have influence from past states which is ignored in [1] and [8].

The authors in [9] establish a method to predict the future states where states are dependent on prior predictions. The model can predict multiple vessel trajectories and their uncertainties. The method depends on the ability to cluster the trajectories. However, the extraction of deep-level data features requires accurate grasp. Excessive extraction will lead to the extraction of useless data features, making the model effect poor.

In [10], authors consider multiple modalities from different sensors. The trajectory prediction network is developed considering AIS data, Radar images, and Electronic Navigational Charts (ENC) images of Inland Shipping dataset. It is shown that prediction error decreases with the use of multi modalities. The absolute trajectory error is 17.13 meters for 50 timestamps and the maximum is around 30 meters.

In this work, a hybrid method is developed to combine the information of generic model and data-driven approach to use the intentions from historical data to calculate precise trajectory predictions.

III. METHODS

A. Predictions using model-based approach

Accurate predictions of ship behavior are required because the ship is operating in rivers, with limited width. To avoid collisions with encountering ships, prediction errors may result into devastating scenarios like collisions. To reduce the errors, accurate estimations are required. In this contribution, it is assumed that position variables from encountering ships are available. Therefore, mathematical models like Abkowitz model [5] which require many variables like rudder angle, heading etc. cannot be used to predict encountering vessel trajectories. An experimental approach has been chosen to decrease the complexity of the model structure. Therefore, the model provided in this contribution has a suitable but minimal number of parameters. The system parameters are obtained by online system identification. The structure of the model is chosen as a third-order system defined in (1) with y as output and u as input as

$$\dddot{y} + a_{33}\ddot{y} + a_{32}\dot{y} + a_{31}y = b_s u. \quad (1)$$

The model is then transferred into state space and extended $\dot{x} = Ax + Bu + K$ and $y = Cx + Du$, where A denotes the state matrix, B the input matrix, C the output matrix, D the transmission matrix, x the state vector, u the input vector

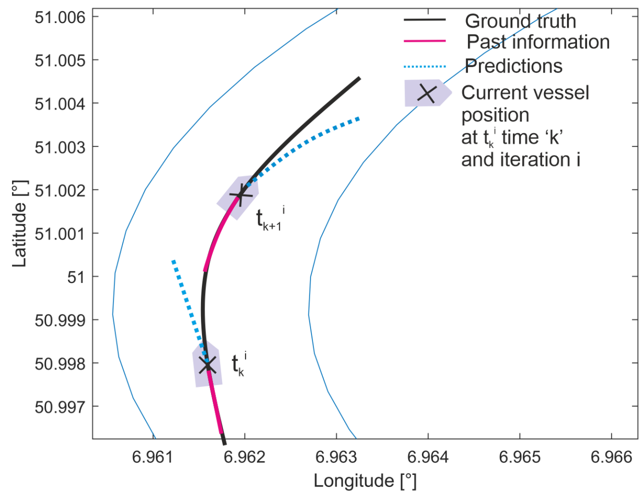


Fig. 2: Sliding window approach is showing local parameter adaption

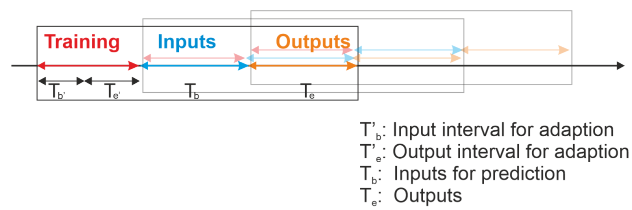


Fig. 3: 1D explanation of sliding window

and y the output vector, and K serves as input matrix of unknown inputs. The extended equation assumes that input u via matrix B is acting to the system as well as unknown input denoted as $b_s u$. The resulting model is therefore composed of the global parameter matrices A, B, C, D as well as the vector K assumed as local adaptable. The unknown matrices A, B, C, and D as well as K have to be identified by a suitable procedure within a first step denoted as data-driven training (identification of parameters). The local parameter b_s is estimated online from time history of the motion of the ship in varying environments. A sliding window approach is used to calculate the local parameter. A window of specified length moves over the data in iterations at time t_k^i as shown in Fig. 3, with T_b' and T_e' denoting the interval length of inputs and outputs for predicting the local parameter b_s. Once the parameter b_s is determined, intentions are predicted for the interval T_e using the input data of interval T_b. The data are fed as an input-output (x_{k-b}, x_{k+1})...(x_k, x_{k+e}) states pair. The same procedure is done iteratively as shown in figure 3. To every ship position at time 't_k' the output belongs to the prediction at time t_{k+e}.

B. Predictions using bayesian approach

Assuming that the historical trajectory data can be clustered, it can be further assumed that the different behaviors of ships can be predicted from the past. The trajectories are clustered based on similarity matrix as shown in [11]. In addition, there are other factors, such as upstream/downstream movement, water level, etc., that influence vessel behaviors. The idea of this paper is to determine the behavior of the considered vessel from historical data by comparing the trajectory of the considered vessel with defined clusters. The most suitable cluster then defines the intended trajectory (as assumed intention) of the vessel. The establishment of the cluster is realized by the Bayes approach. Assuming '*m*' clusters $X_j \in \{X_1, X_2, X_3, ..., X_m\}$ with j denotes the different clusters, the actual trajectory of the considered vessel at time-step *'k'* as $X^{(k)} = \{x_0, x_1, \ldots, x_k\}$, where X are position (Latitude, Longitude), speed over ground, course over ground, etc., variables from time-step 0 till *k*. Applying Bayes recursion, the related trajectory can be obtained by updating the posterior probability using

$$p\left(X_j \middle| \hat{X}^{(k)}\right) = \frac{p\left(\hat{x}_k \middle| \hat{X}^{(k-1)}, X_j\right) p\left(X_j \middle| \hat{X}^{(k-1)}\right)}{\sum_{i=1}^{m} p\left(\hat{x}_k \middle| \hat{X}^{(k-1)}, X_i\right) p\left(X_i \middle| \hat{X}^{(k-1)}\right)}, \tag{2}$$

where $p\left(X_j \middle| \hat{X}^{(k)}\right)$ denotes the posterior probability. The posterior probability is updated by the likelihood and prior probability $p\left(X_j \middle| \hat{X}^{(k-1)}\right)$ at time-step *k-1*. To start the algorithm the initial prior probability is needed. Assuming initial equiprobable clusters

$$p\left(X_j \middle| \hat{X}^{(0)}\right) = \frac{1}{m}, \tag{3}$$

with likelihood $p\left(\hat{x}_k \middle| \hat{X}^{(k-1)}, X_j\right)$ calculated using

$$\begin{aligned} &p\left(\hat{x}_k \middle| \hat{X}^{(k-1)}, X_j\right) \propto \\ &\exp\left(-\frac{1}{2}(x_{k,j} - \hat{x}_k)^T P_k^{-1}(x_{k,j} - \hat{x}_k)\right), \end{aligned} \tag{4}$$

where $x_{k,j}$ is calculated using the search radius. In the search radius a closest point is checked from the clustered trajectories using

$$x_{k,j} = \min x_j \left\{ (x_j - \hat{x}_k)^T P_k{}^{-1} (x_j - \hat{x}_k) \right\}, x_j \in X_j. \tag{5}$$

C. Predictions using combination of model and bayes

In the method illustrated in section III A model prediction methods do not consider future intentions. For example, if the ship is sailing on a curved trajectory, the error increases because there are some parameters on the upcoming trajectory (such as SOG and heading) which are changing (adaption is needed) but not considered by the local model because past information is used. On the other hand, the model adapts to local environmental influences such as local environmental and hydrodynamic effects. The idea of this contribution is now to consider historical information and to combine both models, so that the combined approach is based on i) past information and ii) uses the local model and therefore can project the ship motion more reliably and with less errors.

The approach illustrated in section III B determines the intentions of the considered vessel trajectory using historical data. The suitable cluster calculated by equation (5) defines the next intentions of the associated vessels. This approach does not consider the unmeasured variables like wind velocity and local environmental factors of the current situation. The idea is to consider the historical information and to combine the models, so that the combined approach derives its information from the past and takes the local model into account to consider local environmental and hydrodynamic effects. Furthermore the use of future intentions allows the projection of the ship following the global knowledge. Normally, the intentions at a time-step are predicted using the constant estimated parameters for the prediction zone, but in combined approach the parameters are estimated using the local model and the next intention parameters are used from global Bayes approach. In this approach the estimated local model (this means locally estimated parameters) and future intentions (using Bayes cluster) are combined and used to predict trajectory recursively.

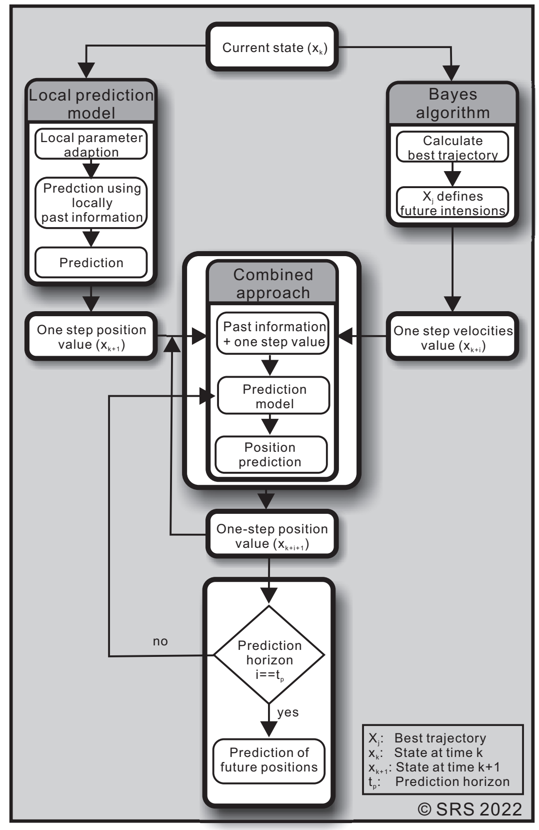


Fig. 4: Combined approach flowchart

The approach is illustrated in Fig. 4. At the current time-step x_k, the prediction model follows the following steps:

- The prediction model adapts the local parameters.
- The behavior of the ship is predicted using local information.
- The predictions contain the error so only one-time step position value x_{k+1} of the model prediction (Fig. 5a) are considered.

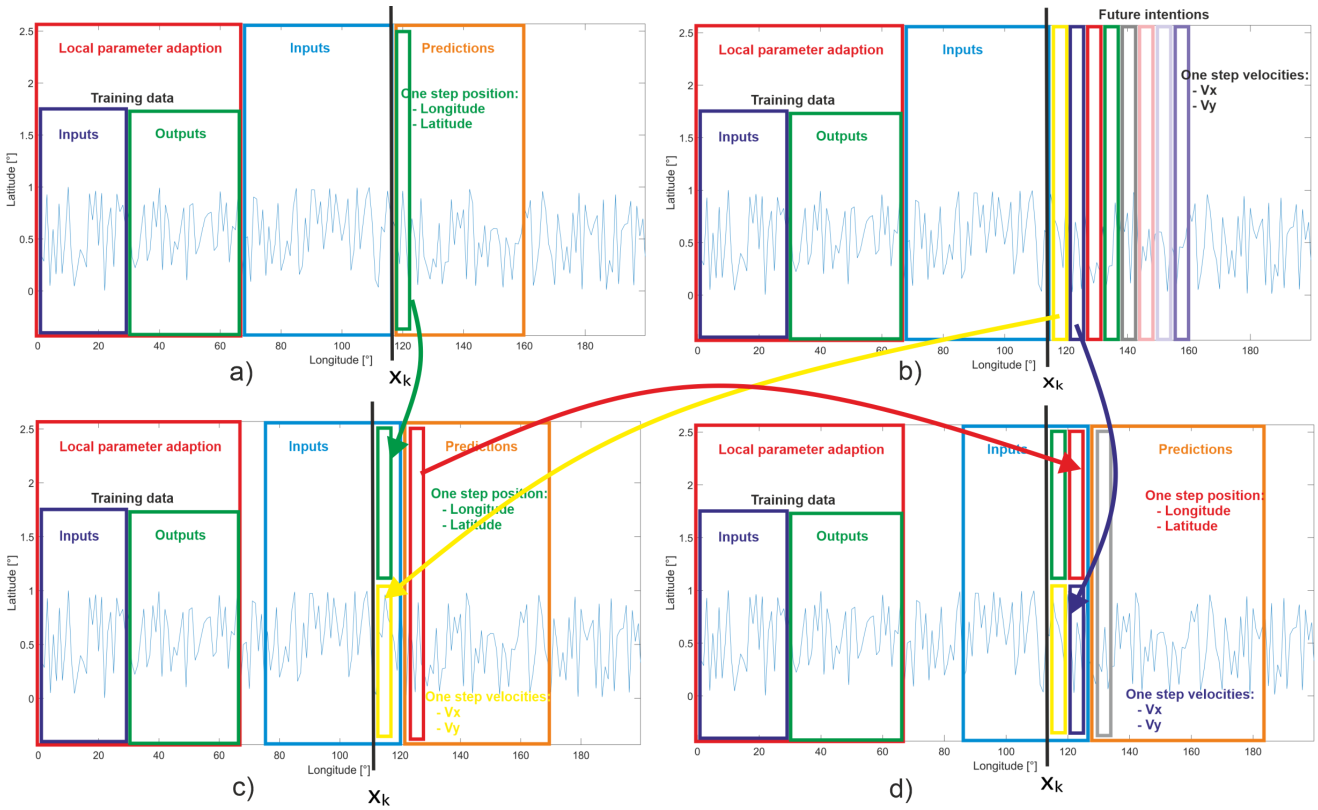


Fig. 5: a) Model prediction definition
b) Best intentions calculated once for the whole prediction horizon
c) and d) Iterative prediction process where the next predictions from local model a) and next intentions from b) are fed to local model to predict the next step.

Here Bayes approach is integrated with the two steps:

- Calculate the best trajectory X_j
- Define X_j as future intentions (Fig. 5b)

The combined approach illustrated in Fig. 4 is working as follows:

1) Combine the positions of the prediction model (Fig. 5a) and the velocities value from Bayes approach (Fig. 5b) of the next time-step
2) Update the inputs to the prediction model
3) Calculate the predictions
4) Repeat the steps 1,2,3 for the prediction horizon

D. Implementation details

The historical AIS data of one year are used to cluster the trajectories for global Bayes approach. The local model parameter estimation is done on MATLAB using online system identification.

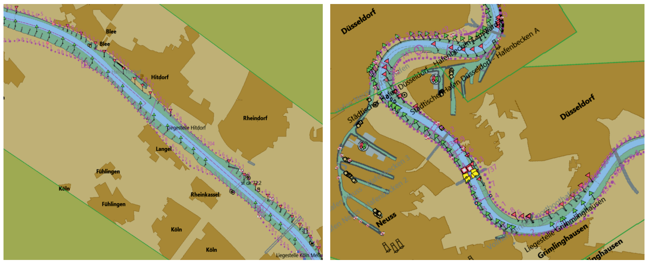
IV. Experimental and Numerical Results

A. AIS- Dataset

To test the approaches the data from a german inland vessel from the 'Prominent Project' [12], [13] are used. The data are provided by 'the Federal Waterways Engineering and Research Institute' (BAW) [14], which were part of the 'PROMINENT' project (Promoting Innovation in the Inland Waterways Transport Sector). The length of the test vessel is 135 meters and the width is 14 meters. The data are transmitted through 27 message types. These messages include the navigational information, such as time, course over ground, speed over ground, position, the IMO number of the ship, actual draft, departure, destination, flow velocity etc. The dataset is a time-series dataset of one year with a sampling rate of one second. The data contain the information of ship sailing in Rhine river in upstream/downstream, loaded/unloaded, and of different water level. It is assumed that data contain different behaviors depending on varying water levels during different seasons.

B. Test cases

Two scenarios are selected to test the models considering the geometrical structure of the Rhine river [15]. The scenarios are straight waterway and curved waterway as illustrated in Fig. 6a and 6b. Two situations upstream/downstream depending on the sailing directions are considered. The vessel sails faster in the downstream direction which results in less (with respect to the geometrical path) resolution compared to the upstream direction. Here, the combined approach discussed in section III C is tested. The prediction horizon 't_p' is



(a) (b)

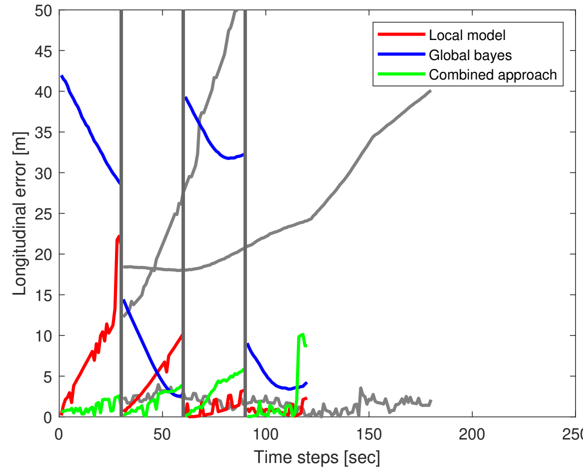
Fig. 6: Two scenarios based on geometry of the Rhine river:
a) the straight path from 703-710 km; and
b) the sharp curved path from 735-745 km

selected to be 180 seconds. The performance of the approach is evaluated by calculating the error $e_x = \|\hat{x}_{k,1} - x_{k,1}\|_2$ between prediction $\hat{x}$ and ground truth $'x'$ for the prediction horizon $\{e_{xk,1}, e_{xk,2}.....e_{xk,180}\}$ at timestep $'k'$. The mean of the prediction error at every timestep of prediction horizon $\{\sum_{n=1}^{k} e_{xn,1}, \sum_{n=1}^{k} e_{xn,2}..... \sum_{n=1}^{k} e_{xn,180}\}$ is taken over the timesteps $'n'$ at which the predictions are done.

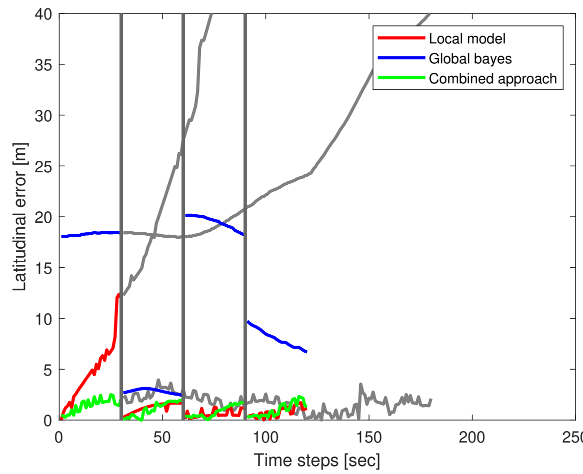
C. Results

Straight waterway: In straight waterway (Fig. 6a), the position errors in case of straight waterway paths are shown in Fig. 7. Vertical lines indicate the local parameter adaption every 30 seconds. The prediction error of first 30 seconds is shown in colors and the next seconds in grey. The results shown in Fig. 7a, indicate that the cross-track error is small and remains almost constant for the combined approach than in comparison to the local and the global Bayes approach. The results also indicates that the error of the local model and global Bayes approaches increases with the prediction time as local model does not consider the future intentions of the ship and considers the parameters constant for the whole prediction horizon whereas Bayes approach considers the closest trajectory and is not the actual trajectory. The error of the Bayes approach changes a lot but the combined approach error remains less than 5 meters for 30 seconds. The error in the combined approach is less because it considers the local environmental factors from model approach and the future intentions from Bayes approach. The along-track error in Fig. 7b also remain below 5 meters.

Curved waterway: In curved waterway (Fig. 6b), the position errors in case of curved waterway paths are shown in Fig. 8. Vertical lines indicate the local parameter adaption every 30 seconds. The prediction error of first 30 seconds is shown in colors and the next seconds in grey. The results shown in Fig. 8a and 8b indicate that the cross-track error and along-track error are less for the combined approach in comparison to the local model and the global Bayes approach. The results also indicates that the error of the local model keeps on increasing as the future intentions are not taken into account by local



(a)



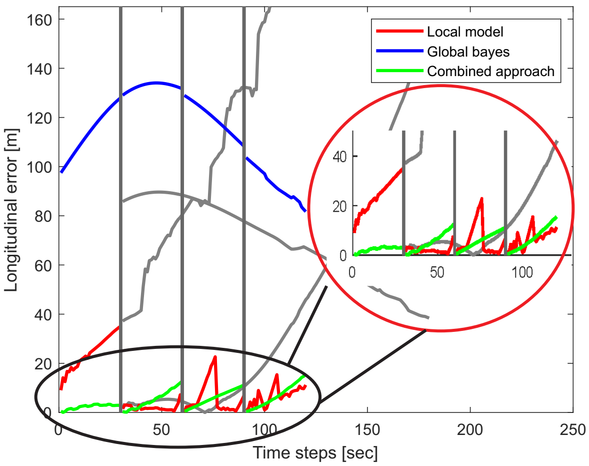
(b)

Fig. 7: a) Mean cross-track error of different approaches in the straight scenario
b) Mean along-track error over the prediction horizon. The vertical lines indicate the time where local parameter is adapted every 30 seconds. The grey lines indicate the predictions from time 31 to 180 seconds

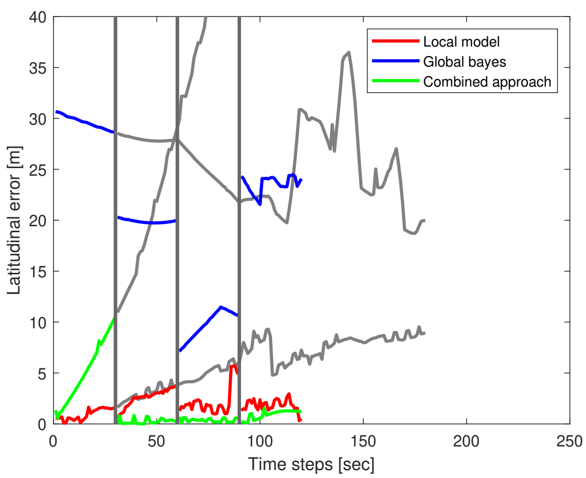
model. It has not considered a curve ahead, whereas global Bayes considers the best intentions from historical data and are used in combined approach. There is a drop in error with prediction horizon in case of Bayes approach because the trajectory belongs to the historical data and the behavior of historical data matches the considered ship at time steps. This is not guaranteed every-time but in combined approach it is guaranteed. While for the global Bayes approach the error changes a lot but combined approach error remains below 10 meters for 30 seconds.

V. DISCUSSIONS AND CONCLUSIONS

The combined approach is developed to predict the trajectories for inland vessels. The performance is compared



(a)



(b)

Fig. 8: a) Mean cross-track error over the prediction horizon in the curved scenario
b) Mean along-track error over the prediction horizon. The vertical lines indicate the time where local parameter is adapted every 30 seconds. The grey lines indicate the predictions from time 31 to 180 seconds

separately in terms of cross-track error and along-track error. It is known that the width of the river is narrow so large error in the prediction time increases chances of collisions. The cross-track error is a relevant parameter in case of overtaking or the ships crossing in parallel. The results shows that the cross-track error is less than 10 meters. The proposed approach performs better than generic model and bayes approach in case of cross-track error but not better than bayes approach in case of along-track error. The approach can be used in detecting the risk of ship collisions. Future work will include the predictions with uncertainties. The approach is tested for short-term predictions and can be extended to test it for long-term predictions. Another step would be to use the data of different ships, where clustering historical AIS data, would be challenging task.

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