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Adaptive situated and reliable prediction of object trajectories

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Autonomous vehicles like inland vessels require reliable information from on-board systems and surrounding objects like encountering vessels in the environment. Besides the detection of objects, the prediction of encountering object's trajectory is one of the most crucial tasks to realize safe operation of autonomous systems. In this contribution, a situated model approach for trajectory prediction as well as an evaluation approach of this model using the Probability of Detection (POD) approach are developed. The reliability of this newly developed prediction model relative to the prediction time is evaluated using the POD approach. The goal is to define the time interval beyond which the reliability is less than the 90/95 (90 % detection probability at 95 % confidence interval) criterion. The decision threshold is defined by the distance needed to avoid collision for the safe sailing of the vessel. The used POD approach provides a new certification standard for prediction approaches and is therefore useful in safety-critical systems. The situated prediction algorithm allows predicting the trajectory of waterway objects for a safety-relevant period of time (minutes) using a simple parameter-based approach where some parameters are globally trained and a local parameter is adapted based on past data using a sliding window approach. The past data consider all local environmental and hydrodynamical effects affecting object's motion in the next minutes. The predictions are assumed as dependent on the different geometry trajectories like straight, curved, and sharp curved paths. The approach uses the position data of vessels (known from AIS or radar data). Experimental data from a German research inland vessel are used to validate the approach. Using the POD-based approach, it can be shown that the local model predictions are reliable in defined time intervals and the reliability of the prediction horizon relative to the locations of the waterways can be defined.

Keywords: POD, Parameter Identification, Reliability, Trajectory Prediction, Autonomous Systems

1. Introduction

Shipping is the mainstay of global trade, as approximately 2/3 of the earth's surface consists of water. Human errors result in 75-96 % of the accidents Gerhard (2012) and thus autonomous ships are an important research topic. The topic of autonomous inland vessels is more challenging compared to sea vessels due to narrow distance required in applications like overtaking other vessels or passing under a bridge Volkova et al. (2021). Object detection and trajectory prediction modules are useful for autonomous vessels. Besides object detection, trajectory prediction is also important for collision avoidance. Thus, autonomous inland vessels need the intentions of surrounding vessels and moving objects. Vessels operating in narrow fields like rivers, channels, among others require high accuracy of intention prediction. Besides high accuracy, reliable information is also required.

A standard performance measure has not yet been defined for trajectory prediction approaches. Evaluation and quantization of the performance of approaches are challenging tasks for trajectory prediction. In Graser et al. (2019) the along-track error and cross-track error approach is explained. The cross-track error reflects the true movement direction of the vessel. 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. Similarity measure for trajectory prediction evaluation is explained in Quehl et al. (2017). Mean Euclidean distance (MED) in Bashir et al. (2007) is used to define a point in time for each trajectory from which onwards the comparison starts. Dynamic Time Warping (DTW) is proposed in Keogh and Pazzani (2000) as a trajectory measure on general time series. The longest common subsequence (LCSS) measure (Buzan et al.,

2004) is a trajectory measure that evaluates for how many time steps two trajectories are matching each other. CLEAR multiple object tracking accuracy (CLEAR-MOTA) (Bernardin and Stiefelhagen, 2008) is used to evaluate usually the tracking algorithms but can also be used for prediction evaluation by defining the matches for each predicted point similar to the LCSS measure so that the accuracy can be calculated. The trajectory Hausdorff similarity measure (THAU) in Lee et al. (2007) describes a path measure approach that consists of a weighted sum of several path distances like, position and orientation, etc. to consider the different aspects of the path. The drawback of this similarity measure is bias-based on the data set. Second, the approach is partly based on the assumption that features that are suitable to use for prediction are also features that are predicted well.

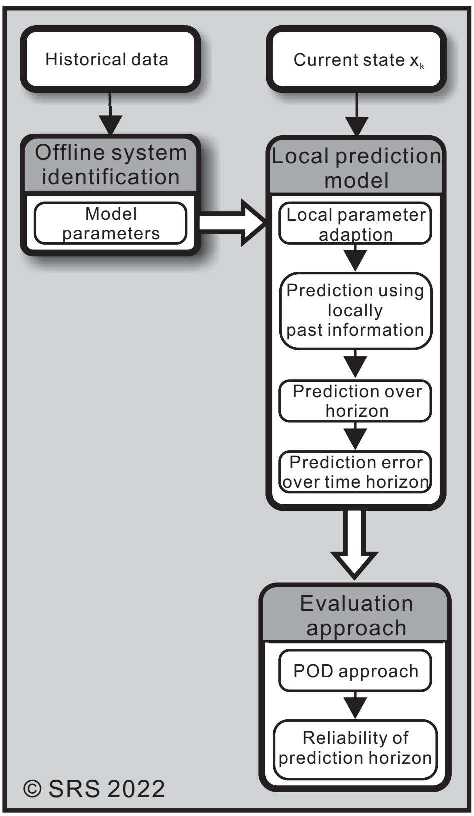

Fig. 1. The developed approach

A measure typically used to quantify the reliability of Nondestructive Testing (NDT) procedures (Annis, 2009), Structural Health Monitoring systems (SHM) (Ameyaw et al., 2020), and lately classification approaches (Ameyaw et al., 2022) is the Probability of detection (POD) measure. The POD is a diagnostic tool as well as a reliability measure and takes into account statistical variability of sensors and measurements properties. Later model-assisted POD (MAPOD) (Knopp et al., 2007) is developed to improve the effectiveness of POD models relative to time and cost. In this contribution, the POD approach is implemented to define the time interval with which the prediction is reliable relative to determned decision threshold.

A simple parameter-based approach is developed in (Thind and Söffker, 2022) to model the Ship and Average Displacement Error (ADE) over the prediction horizon as an evaluation measure and is explained in figure 1. In this work AIS data from a german inland vessel from the 'Prominent Project' (Orlovius and Christin, 2017) are used. The model performance depends on different parameters like data quality, different sampling time, environmental factors, and different operating situations. The ADE parameter does not allow to completely define the model reliability, as other parameters which are not considered might affect the model performance.

The principal challenge relative to safety-critical applications is the limited guarantee when approaches are applied to input data that are not fully known. The prediction error depends on various parameters such as curve geometry. Defining thresholds and calculating the time frames for which the predictions are less accurate cannot be done using existing approaches because the ground truth is not available during real applications and the reliability of predictions is not assured. The POD approach is introduced to overcome these limitations. The POD is a diagnostic tool as well as a reliability metric. It is a probabilistic method that allows researchers to evaluate the performance of monitoring techniques by estimating the sensitivity and reliability of sensors and measurement properties (Annis, 2009). The tool commonly used for expressing the reliability is the POD curve. It is constructed by plotting the accumulation of targets detected against the target characteristic (size, length, depth, etc.). A typical certification standard in safety-critical systems is the 90/95 measure which represents 90 % detection probability at 95 % confidence interval. The POD reliability measure is used in this contribution as a reliability measure and also as a diagnostic tool to assess the effect of the prediction horizon relative to the prediction time.

The article is organized as follows: in section 2 the simple parameter-based approach is briefly introduced, followed by the newly developed POD reliability measure to define the time interval beyond which the reliability is less reliable using the 90/95 criterion in section 3. The experimental and numerical results are explained in section 4 and in the section 5, summary and conclusion are given.

2. Predictions using model-based approach/ Simple parameter-based approach

For the safety of vessels, collision avoidance is an important module which requires accurate trajectory predictions in the case of autonomous vessels with respect to the behavior of other objects. An accurate approach is required to realize trajectory prediction. In this contribution, it is assumed that only position measurements of encountering ships are available. Thus developing a model based on position measurements is discussed in this section. The developed model should not be complex and must be real-time applicable. The model-based trajectory prediction method is developed and it requires an accurate ship model in different environmental conditions. Models should be robust, so that it can be applied in trajectory prediction, localization and model-based control applications. Due to the nonlinear relations between hydrodynamics and complex rigid motion behavior of the ship, the modeling process is complex.

A suitable simple parameter-based approach with minimal number of parameters is developed in (Thind et al., 2022). The system parameters are obtained by online system identification. A third-order system (1) defines the model with y as output and u as input as

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

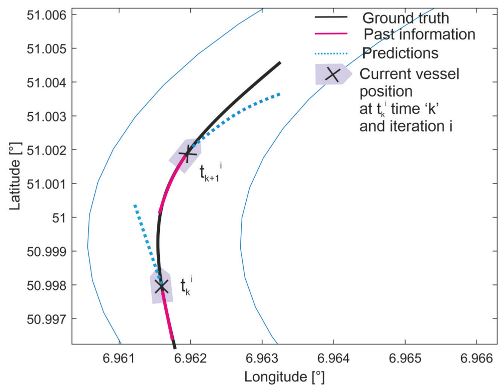

Fig. 2. Sliding window approach with showing local parameter adaption

Thind and Söffker (2022)

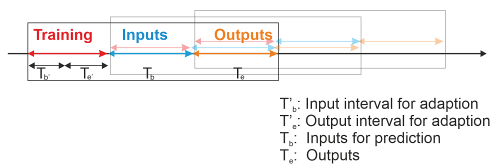

Fig. 3. 1D explanation of sliding window

Thind and Söffker (2022)

A state space model $\dot{x} = Ax + Bu + K$ and $y = Cx + Du$ is used, 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 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 $k_s u$. 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 k_s is estimated online from time history of the motion of the ship in varying environments. A sliding window approach is used to continuously calculate the local parameter *K*. 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}.

3. Probability of detection

Probability of detection is a certification tool used to access the reliability of NDT/SHM measurement procedures. Data used in producing POD curves are categorized by the main POD controlling variables. These variables are either discrete or continuous and can be classified as

(1) Hit/miss: produce binary statement or qualitative information about the existence of a target.
(2) Signal-response: systems which also provide some quantitative measure of target.

The data used in this work is continuous therefore the signal-response method will be used.

3.1. *Signal-response approach to POD*

The signal response approach is used when a relationship between an increasing function and a corresponding varying parameter exists. In the derivation of the signal-response POD function, a regression analysis of the observed or computed data has to be realized (Fig. 4) (Annis, 2009). The regression equation for a line of best fit to a given data set is given by

$$y = b + mx, \tag{2}$$

where *m* is the slope and *b* the intercept. The Wald method is used to construct the confidence bounds. Here the 95 % confidence bounds on *y* is constructed by

$$y_{(a=0.95)} = y + 1.645\tau_y, \tag{3}$$

where 1.645 is the *z*-score of 0.95 for a one-tailed standard normal distribution and τ_y the standard deviation of the regression line. The Delta method is a statistical technique used to transition from regression line to POD curve (Annis, 2009). The confidence bounds are computed using the covariance matrix for the mean and standard deviation POD parameters μ and σ respectively. To estimate the entries, the covariance matrix for parameters and distribution around the regression line needs to be determined. This is done using the Fisher's information matrix *I*. The information matrix is derived by computing the maximum likelihood function *f* of the standardized deviation *z* of the regression line values. The entries of the information matrix are calculated by the partial differential of the logarithm of the function *f* using the parameters of $\Theta(m, b, \tau)$ of the regression line. From

$$z_i = \frac{(y_i - (b + mx_i))}{\tau} \tag{4}$$

and

$$f_i = \prod_{i=1}^{n} \frac{1}{2\pi} e^{-\frac{1}{2}(z_i^2)} \tag{5}$$

the information matrix *I* can be computed as

$$I_{ij} = -E(\frac{\partial^2}{\partial\Theta_i \partial\Theta_j} log(f)) \tag{6}$$

The inverse of the information matrix yields ϕ as

$$\phi = I^{-1} = \begin{bmatrix} \sigma_b^2 & \sigma_b\sigma_m & \sigma_b\sigma_\tau \\ \sigma_m\sigma_b & \sigma_m^2 & \sigma_m\sigma_\tau \\ \sigma_\tau\sigma_b & \sigma_\tau\sigma_m & \sigma_\tau^2 \end{bmatrix} \tag{7}$$

The mean μ and standard deviation σ of the POD curve are calculated by $\mu = \frac{c-b}{m}$, where *c* is the decision threshold and $\sigma = \frac{\tau}{m}$. The cumulative distribution Φ is calculated as

$$\Phi(\mu, \sigma) = \frac{1}{2}\left[1 + erf\frac{x - \mu}{\sqrt{2}\sigma}\right]. \tag{8}$$

The POD function is derived as

$$POD(a) = \Phi\left[\frac{a - \mu}{\sigma}\right]. \tag{9}$$

Using this formula, the POD-curve can be set up for varying parameters. For this example, the varying parameter is the time horizon. The intercept $\hat{\beta}_0$ and slope $\hat{\beta}_1$ are statistically estimated from the observations/measurements.

4. Evaluation approach

As explained in section 3.1, the signal-response method is used when a relationship between a changing parameter and an evolving function or response. The input to the approach is predictions over time horizon of 180 s and constitutes the changing parameter. For every second the corresponding error between the actual trajectory and the prediction model in meters is evaluated. The error is in the latitude x and longitude y directions. The relation $\sqrt{x^2 + y^2}$ is computed to obtain a single representation of the error.

4.1. *AIS- Dataset*

To test the approaches the data from a german inland vessel from the 'Prominent Project' Orlovius and Christin (2017) are used. The data are provided by 'the Federal Waterways Engineering and Research Institute' (BAW) (Orlovius and Christin, 2017), which were part of the 'PROMINENT' project (Promoting Innovation in the Inland Waterways Transport Sector supported by Horizon 2020 programme, European Commission). The length of the test vessel is 135 meters and the width is 14 meters. The data are transmitted through 27 message channels. These messages include 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 consists of time-series data of one year with a sampling rate of one second. The data contain information about sailing on the Rhine river in upstream/downstream, loaded/unloaded, and of different water level. It is assumed that the data contain different behaviors depending on varying water levels during different seasons. To test the POD approach, the euclidean distance error is calculated over the prediction horizon of 180 seconds using approach explained in section 2. The ADE error serves as the response to the prediction horizon (target).

4.2. *POD generation process*

Based on the computed response values, the signal-response method is utilized in this section to generate the POD. The aim is to establish a POD characterization to illustrate reliability of the prediction horizon. Four models comprising combinations of logarithmic and linear scales (Fig. 4) are established to ascertain model described by a straight line and approximately constant variance. The criteria for a valid model are (Annis, 2009)

i. Linearity of the parameters: $E(y_i|X) = x_i\beta$, where x_i is the $i - th$ row of X,
ii. Uniform variance: $var(y_i|X) = \sigma^2, i = 1, 2, 3, ..., n$ and
iii. Uncorrelated observations: $cov(y_i, y_j|X) = 0, (i \neq j)$.

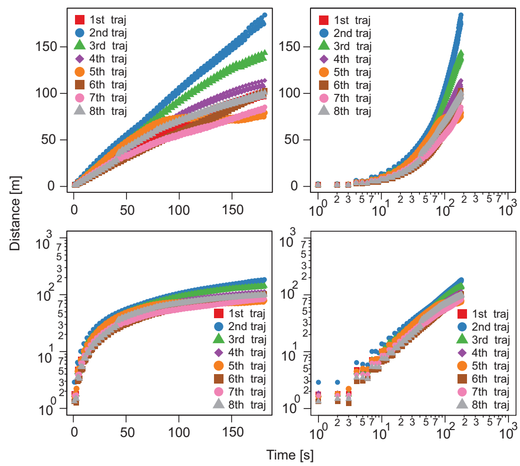

Fig. 4. Regression models a: x vs. y b: log x vs. y c: x vs. log y d: log x. vs. log y

In this example, the model that best describes the above criteria is the log-log plot (model 4 d) and is therefore selected for further analysis. Regression analysis is implemented on model 4 b using maximum likelihood estimation as it is better suited for censored data in comparison to known methods like ordinary least squares.

The inspection threshold (minimum detectable data), saturation threshold (maximum detectable data), decision threshold, confidence bounds, and prediction bounds are constructed using the formulation from section 3.1 as illustrated in Fig. 5.

Accordingly, the confidence bounds serve as certification criteria, while the prediction bounds

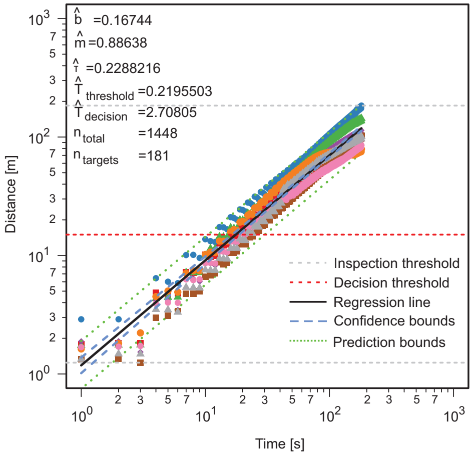

Fig. 5. Data distribution for logarithmic scale.

serve as boundaries to ensure that of every 100 new observations, 95 should fall within them. Additionally, cumulative density functions (CDFs) are constructed for the data distribution. Based on the CDF area above the threshold, the POD curve is generated (Figure 6).

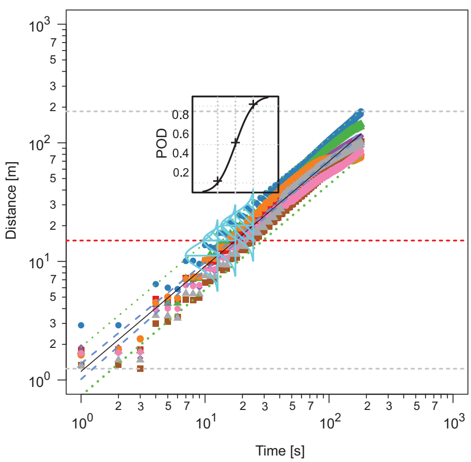

Fig. 6. Regression analysis.

The POD curve is analogous to the regression line. The confidence bounds about the regression line are used to construct the 95 % bounds around the POD curve. The POD curves corresponding to each trajectory for loaded downstream condition are shown in Fig. 7. The 90/95 POD value $T_{90/95}$

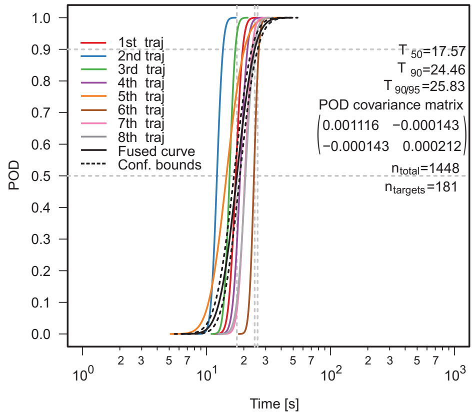

Fig. 7. POD curves for loaded downstream.

for trajectory 1 is 20.06 s. This implies for a decision threshold of 15 meters, the model is able to predict accurately till 20.06 s beyond which the prediction horizon is inaccurate with 90 % probability with a 95 % reliability. Seven other trajectories for loaded downstream condition are analyzed.

The procedure is repeated for three other conditions namely upstream loaded, downstream unloaded, and upstream unloaded. The corresponding 90/95 POD values are shown in Tab. 1.

Traj.	Loaded downstream POD [s]	Loaded upstream POD [s]	Unloaded downstream POD [s]	Unloaded Upstream POD [s]
1	20.06	22.91	24.94	20.42
2	13.90	29.45	22.30	27.04
3	17.43	21.66	17.86	26.46
4	21.92	19.31	25.56	25.50
5	21.57	21.19	22.63	21.18
6	26.83	16.39	23.82	25.24
7	23.87	17.86	25.17	20.34
8	24.91	23.13	21.06	24.33

The results in Table 1 show the time horizon for each track for which the prediction is considered to be reliable with the 90/95 certification criterion. This will be particularly helpful in the context of autonomous navigation because a safe prediction horizon can be defined for each trajectory and scenario therefore helping define safe distance and interaction between vessels. The introduced approach permits a new POD-based certification and comparison method for prediction models. Evaluation of prediction models relative to prediction time horizon is not possible using known and existing measures introduced in the literature review. However the introduced POD approach makes it possible to statistically determine a set point (here: 90/95 criterion) beyond which the prediction is not reliable in the aforementioned sense.

5. Conclusion

In this contribution a new evaluation measure on the performance of prediction models using POD approach is presented. The safety distance required for the collision-free sailing of vessels defines the threshold. The reliability of the model is determined for the prediction horizon under which it is known that the predictions will be always 90 % under the defined error limit at a 95 % confidence level. This is needed because the evaluation process of known approaches are non-parametric and hence not suitable to evaluate the effect of process parameters on prediction horizon. The results indicate the model performance and prediction reliability changes in different situations/conditions. As a result, the local parameter must be adapted at variable duration, and the effect of other process parameters should also be considered.

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