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An Optimal Study on Non-Uniform Sampling Target Motion Parameters Calculation Method Integrated with STC-BiLSTM

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Abstract: In recent years, with the complexity of Marine traffic and the popularization of asynchronous sensor acquisition, the prerequisite of traditional uniform sampling is broken, and the data time series presents the non-uniform characteristics of "disordered time interval and dense mutation features", which makes the Marine moving target calculation face more and more challenges of non-uniform sampling data. In order to cope with the shortcomings of traditional methods in abrupt change modeling and time structure adaptability, this paper systematically analyzes the key influencing factors based on a large number of simulation data, and designs a hybrid model architecture with the ability of short-term abrupt change response and long-term dependence modeling. In this paper, we propose a hybrid deep regression model (STC-BiLSTM-Attention) that integrates spatio-temporal convolution, bidirectional LSTM and attention mechanism, which can realize high-precision adaptive calculation method optimization. The model uses SCT module to extract local spatio-temporal features, BiLSTM to model long-range dependence, and self-attention mechanism to focus on key time points, so as to enhance the modeling ability of nonuniform sequence. The experimental results demonstrate that the proposed method achieves an average prediction accuracy of 89.75% across five independent datasets. In scenarios characterized by non-uniform sampling and high dynamic maneuverability, the position calculation error rate is reduced to 8.52%, which is substantially lower than that of the Kalman filter (21.36%) and the manual calculation approach (27.84%). Ablation studies further validate that the synergistic interaction between the STC module and the attention mechanism significantly enhances model accuracy. This highlights the method's superior capability in addressing tasks involving both short-term abrupt changes and long-term dependencies, thereby offering robust technical support for auxiliary decision-making under complex maritime conditions.

Keywords: Target Motion Parameters Calculation; STC-BiLSTM; Non-uniform sampling

1. Introduction

With growing global marine activities, accurate calculation of marine moving targets is vital for marine security, resource development, and environmental monitoring. However, constrained by observation equipment, environmental factors, and unstable data transmission, actual marine target time-series data often has issues like non-uniform sampling[1], data loss[2], and noise[3], posing significant challenges to traditional methods.

Traditional maritime target solvers largely depend on manual plotting[4], working effectively under complete, uniformly sampled sequential data. However, during missing calculation elements or target maneuvers, errors often become excessive, requiring manual re-selection of schemes. Yet manual experience struggles to fully anticipate algorithm-specific errors under unique conditions, limiting tracking accuracy and system response speed.

Researchers thus propose statistical models like Kalman filter[5] and particle filter[6], which excel in handling uniformly sampled data to minimize manual intervention in maritime target solving. However, their performance degrades significantly under non-uniform sampling and complex maneuvers. Recent deep learning advancements offer new perspectives for time-series modeling: CNN and LSTM excel in extracting spatial-temporal features, with ConvLSTM—integrating convolutions into LSTM—widely applied in weather[7] and traffic flow prediction[8] to achieve notable results.

In marine target detection, researchers explore deep learning applications. Wang et al[9] developed SALA-LSTM, a deep learning-based marine radar detection method, enhancing local feature perception via adaptive convolutions to boost accuracy in complex seas. Yang et al[10] integrated attention with ConvLSTM for coastal water level prediction, improving accuracy and real-time performance significantly. Sani et al[11] merged radar, AIS, and optical data via GCN to model ship interactions for multi-target trajectory prediction. Existing methods often rely on interpolation/resampling for non-uniform data, risking information loss or higher complexity; adaptive sampling strategies optimize data collection but don't solve non-uniform calculation directly. Chen et al[12] proposed FRA-LSTM, fusing forward/reverse subnetworks and attention to capture trajectory timing features for better prediction. Zhou et al[13] designed an LSTM model with trajectory correlation and temporal attention, filtering redundancies via attention to enhance key feature capture and prediction performance. Li et al[14] improved YOLOv7-Tiny with RepVGG and feature fusion for better small-target radar detection, though it lacks adaptability to non-uniform sampling.

In non-uniform time-series processing, deep learning has seen breakthroughs. For medical data, Wang et al[15] proposed two approaches: missing data imputation (e.g., multiple imputation) and direct modeling (e.g., TCN). TCN uses dilated convolutions to capture long-term dependencies but lacks spatial feature fusion. In marine applications, Zhang et al[16] applied RC-LSTM for China's offshore SST spatio-temporal prediction, using convolutions for spatial features and LSTM for time-series, though non-uniform sampling robustness needs improvement. Attention-enhanced models like Bommidi et al[17]'s TCN-BiLSTM boost wind speed interval prediction accuracy via dynamic time-step weighting, yet adaptive capacity in dynamic environments remains limited.

Despite advancements in respective fields, limitations remain in handling non-uniform marine target time-series data. Non-uniform sampling introduces temporal discontinuities, challenging direct application of traditional models. Meanwhile, highly nonlinear and uncertain maritime target motions make it difficult for single models to fully capture dynamic characteristics.

To address these challenges, this study proposes STC-BiLSTM-Attention, a hybrid deep regression model integrating Spatio-temporal Convolution (STC), Bidirectional LSTM (BiLSTM), and attention mechanisms for precise estimation error prediction. 2D convolutions first extract local spatio-temporal dependencies to enhance short-term dynamic perception. Stacked BiLSTM then models long-range dependencies, paired with self-attention to highlight critical time steps and improve responsiveness to key moments. Finally, LSTM compresses sequences, with fully connected layers outputting error predictions. This architecture balances local detail extraction and global dynamic modeling, suitable for ship prediction error modeling in complex environments.

This method integrates spatio-temporal convolution's spatial feature extraction, BiLSTM's time-series modeling strengths, and attention mechanisms' key feature focusing to effectively handle non-uniform time-series data, enhancing maritime target solving accuracy and robustness. Experiments on simulated/real datasets demonstrate its superior performance in processing non-uniform data and capturing complex target motions, offering a novel solution for maritime target solving.

2. Spatio-temporal Convolutional Bidirectional LSTM Attention Network

2.1 Bi-LSTM Model

Bi-directional Long Short-Term Memory network (Bi-LSTM) uses the parallel architecture of forward LSTM ($\overrightarrow{LSTM}$) and backward LSTM ($\overleftarrow{LSTM}$) to construct a bidirectional temporal dependence modeling system. Among them, the forward LSTM transmits information forward along the sequence to extract the feature dependencies of historical moments. The backward LSTM backtracks along the sequence to mine the influence of future moments on the current state. This bidirectional information interaction mechanism enables the model to fully integrate contextual semantic information and significantly improve the feature expression ability of sequence data.

The core gating mechanism of Bi-LSTM consists of a forgetting gate, an input gate and an output gate. Each gating unit outputs the value of the interval $[0,1]$ through the $sigmoid$ activation function to realize the dynamic regulation of the information flow.

The synergistic effect of the gating mechanisms effectively overcomes the problems of gradient disappearance and gradient explosion in traditional recurrent neural networks, so that it shows excellent performance in long sequence data processing and can accurately capture complex time series dependencies.

Compared with one-way LSTM, the hidden state $h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$ of Bi-LSTM realizes the deep fusion of historical and future bidirectional information. In the dynamic modeling of ship maneuvering process, the proposed architecture can simultaneously capture the route planning information before turning operation (future dependence) and the state evolution characteristics after operation (historical dependence).

2.2 Self-attention Mechanism

As a key deep learning technology, the self-attention mechanism leverages the Query-Key-Value (QKV) architecture to model temporal correlations in sequences, inspired by human cognitive selective attention for dynamic key information capture in massive data. It first maps input sequences into three vector spaces: Query initiates retrieval via targeted queries, Key serves as an information index for unique identification and efficient lookup, and Value contains the actual features to be aggregated.

For similarity calculation, dot product or cosine similarity measures Query-Key associations. To address gradient vanishing from high dimensions, Scaled Dot-Product Attention normalizes dot products by $\sqrt{D}$ (vector dimension) via Softmax, generating attention weights that reflect timestep importance in the task—higher weights indicate greater contribution. Finally, weighted summation of Values adaptively aggregates sequence information, capturing long-range dependencies and dynamically focusing on critical timesteps to enhance complex sequence processing.

2.3 Spatio-Temporal Convolutional Layer (SCT)

The spatio-temporal convolutional layer (SCT) serves as the model's core for handling multi-dimensional time-series data. Via temporal local feature extraction and spatial cross-feature correlation modeling, it enables multi-scale analysis of maritime target motion states. Designed to align with the spatio-temporal coupling nature of ship motion—e.g., course-change/position-offset dynamics, speed-adjustment/time-interval correlations—it feeds high-quality inputs with local details and cross-feature dependencies into subsequent BiLSTM layers for long-range dependency modeling.

SCT's core advantage lies in deep spatio-temporal feature coupling. Temporally, 5- and 3-step convolution kernels adapt to varying ship maneuver durations. Spatially, kernels process multi-dimensional sensor data to model geometric relationships between position offset, speed, heading, and time intervals (e.g., heading's impact on position offset at constant speed). The final T/2×192 feature map—concatenating 64+128 channels from two convolutional layers—transforms non-uniform data into hierarchical spatio-temporal semantic representations.

Unlike traditional TCN focusing on long-term time-series dependencies, SCT prioritizes local mutation analysis of multi-feature time-series data. Its 1D convolutions eschew causal constraints/dilation, instead adapting to non-uniform time intervals and sensor feature spatial correlations via multi-scale kernel groups and pooling. This design enables SCT to better capture instantaneous cross-feature correlations (e.g., heading shifts with position jumps during sharp turns) in short-term abrupt change scenarios like ship maneuvers—scenes where TCN's strength in uniform long-series trend prediction is less applicable.

As the first stage in the model's three-level processing pipeline, SCT is critical for feature preprocessing, scale adaptation, and pattern separation. It first converts 12D raw data into spatio-temporal semantic feature maps, filtering noise and enhancing key motion features. Second, pooling downsamples time steps from 20 to 10 to meet Bi-LSTM computational efficiency needs. Finally, it distinguishes constant velocity (low activation) and maneuvering (high activation) segments via feature response intensity, providing key timestep cues for the self-attention layer. This design enables SCT to form an efficient collaborative chain with Bi-LSTM and self-attention—from local spatio-temporal feature extraction to long-range dependency modeling and dynamic key information focusing—to jointly address complex maritime motion solving challenges.

2.4 Spatio-Temporal Convolutional Bidirectional LSTM Attention Network (STC-BiLSTM-Attention)

However, Bi-LSTM, self-attention mechanism and TCN still have limitations when applied separately. The organic integration of the three can give full play to their respective advantages and effectively solve the problem of solving moving targets at sea under non-uniformly sampled time series data.

Building on this, we construct the STC-BiLSTM-Attention network to achieve more accurate target solutions. While Bi-LSTM, self-attention, and TCN excel in their domains, single models face limitations with non-uniform marine target data: Bi-LSTM lacks explicit time interval modeling, self-attention may overlook long-interval key info, and TCN struggles with irregular time interval changes. By organically integrating their strengths, the proposed STC-BiLSTM-Attention network effectively addresses non-uniform sampling challenges, enhancing solving accuracy and robustness for maritime motion targets.

Aiming at ship behavior in multivariable dynamic sequence of complex evolution process and calculates the error prediction of nonlinear characteristic, this paper proposes a Spatio-Temporal Convolution (STC) network combined with Bidirectional Long Short-Term Memory (BSTM) network. BiLSTM) mixed with Attention mechanism (Attention) of neural network structure, referred to as on STC - BiLSTM - Attention. This structure can simultaneously model global change pattern and local temporal dependence, and automatic focusing on the key segments of time, so as to improve prediction accuracy and generalization ability model.

This model consists of the following five main modules:

(1) Input layer and data preprocessing

The input is a multi-dimensional feature sequence in a time window with the shape (T,F), where T is the time step (e.g., 20) and F is the number of key variables after feature selection (e.g., 10). All feature values are normalized by MinMaxScaler, and the target variable (estimation error) is also standardized to facilitate the stable training of the model.

(2) Spatio-Temporal Convolutional Module (STC)

For mining the short-term time change and characteristics between local coupling mode, first will reshape the input sequence for the three-dimensional tensor, then USES the two-dimensional convolution (Conv2D) slide for joint operations. (T,F,1) This convolutional layer can be regarded as a filter acting on both time and variable dimensions to identify "behavior patterns" in local feature segments. Through MaxPooling2D down sampling, compression time step of information redundancy and denseness of enhanced features expression.

(3) Bidirectional LSTM module (BiLSTM)

To capture ships path dependency information for a long time, the evolution of network design for two layer stacked two-way LSTM, node contains 128 and 64 units, respectively. The structure on the direction of forward and reverse two times of coding sequence information, effectively ease the one-way LSTM information loss problem. Each layer after joining Dropout layer (discard rate 0.4), in order to enhance robustness of the model and prevent the fitting.

(4) Self-Attention

Due to the different time points in the time series is finally forecast the influence degree of the inconsistent, model introduced from attention mechanism, the output power of the LSTM layer with distribution, which focused on the key dynamic characteristics of the time period. Attention results with original LSTM output for Mosaic (Concatenate), in the ability of said while maintaining the original time structure information.

(5) The Output Layer

After joining together, the time sequence of said further through a layer of LSTM unit (32) is compressed, then output by the Dense layer as a continuous value target variable (that is, the calculation error) prediction results. Model USES the mean square error (MSE) as a loss function training, the optimizer for adaptive vector of Adam.

On average, on STC - BiLSTM - Attention model both said ability strong, full time structure modeling, feature advantages of self-focusing, suitable for deployment in intelligent aided decision-making system, maritime simulation platform and anomaly detection, etc. The actual application scenario. Its specific structure as shown in Figure 1.

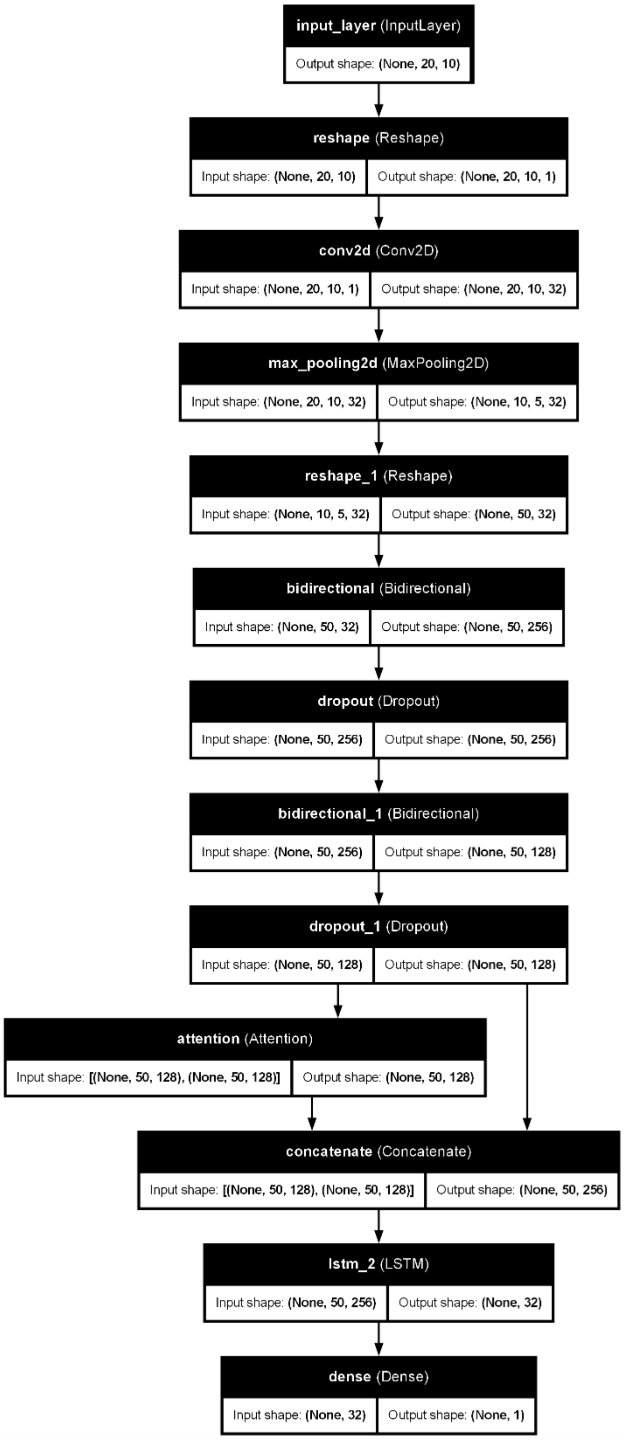

Figure 1: Method Flow of The Model Constructed in This Paper.

3. Simulation Data Generation Model

3.1 Overview of Model Setup

Data generation module is designed to simulate non-uniform sampling trajectory of the sea ship, generates true state (position, speed, heading), mobile label direct flights (constant speed, steering, deceleration) and observation error (distance, direction, azimuth) of multidimensional data set. Module through parametric configuration, random event injection, dynamic error modeling methods, such as repetition of the complexity of the real-ship motion in the scene with non-uniform sampling feature, for subsequent target training and validation of the calculating model provides high quality data to support.

3.1.1 Overall Process Structure

The whole data generation process revolves around the generation of ship track. Each round of simulation generates a pair of ship trajectories, calculates the relative relationship in space and time, labels the segment information, and injects the observation error related to the target distance. In the end, after the amount of data required, system incorporating simulation results for structured data table, so that subsequent calls and algorithm evaluation model using. The key components of the process include trajectory generation, behavior injection, temporal sampling, location calculation, state alignment, label generation, and observation error modeling, as detailed in Figure 2.

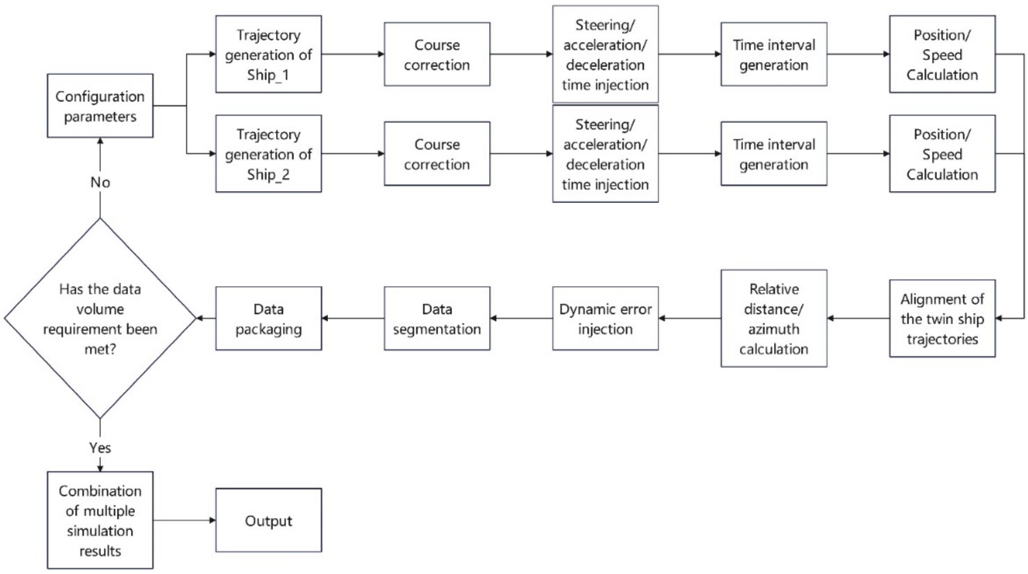

Figure 2: Data Generation Module Architecture Diagram.

3.1.2 Flight Path Simulation

The trajectory of each vessel is by default composed of $N \leq 1200$ discrete time steps, sailing for approximately 20 minutes. The initial heading Angle θ_0 is uniformly sampled from the interval $[0,2\pi)$, and the initial speed v_0 is randomly selected from the set range $[v_{\min}, v_{\max}]$. These parameters determine the initial direction of motion and propulsion speed of the ship, ensuring that each simulation is different from the other.

The course angle and speed of the ship can be dynamically adjusted in the flight, formation has the characteristics of trajectory. All state variables (position, speed, heading, mobile) are updated in each time step, and ultimately the organization is structured sequence data.

3.1.3 Modeling Maneuvering Behavior

In order to simulate the motion diversity of the actual ship, the system randomly injected steering or acceleration and deceleration events during the trajectory generation. The steering behavior is realized by adjusting the heading Angle within a certain time window, and the Angle variation range is set to $[15°, 45°]$,and the number of continuous steps is set to $T_{turn} = 100 \pm 20$.

Heading angle of the angle of the increment/decrement for each step:

In trajectory stochastic trajectory diversity, to enhance system into a turn or deceleration behavior. Among them:

The Angle change of the steering behavior is:

$$\Delta\theta = \frac{\Theta_{\text{total}}}{T_{\text{turn}}}$$

The speed increment of the acceleration and deceleration behavior is:

$$\Delta v = \pm\alpha \cdot v_0 \quad (\alpha = 0.2)$$

The duration of both types of behaviors was $T = 100 \pm 20$ steps, and the interval between behaviors was maintained at least 100 steps.

3.1.4 Spatial Advance and Position Calculation

Position update based on the current course Angle and speed, track is advancing through the current course Angle and speed calculating two-dimensional position change, perspective transformation is as follows:

$$\phi_t = 90^\circ - \theta_t$$

Displacement updating formula is:

$$x_{t+1} = x_t + \text{clip}(v_t \cdot \cos\phi_t)$$
$$y_{t+1} = y_t + \text{clip}(v_t \cdot \sin\phi_t)$$

Where $clip()$ represents the limit on the maximum moving distance in a single step, which is used to limit the maximum moving distance in a single step to not exceed the set value (such as 2.0 meters) to avoid the jump change in the simulation results.

3.1.5 Relative State Calculation

For each time sampling point, the system calculates the spatial relationship between ship 1 and ship 2, which includes two key variables:

Relative distance: $\boldsymbol{d_t}$

$$d_t = \sqrt{(x_1^t - x_2^t)^2 + (y_1^t - y_2^t)^2}$$

Relative azimuth: $\boldsymbol{\beta_t}$

$$\beta_t = [atan2(x_1^t - x_2^t, y_1^t - y_2^t)] \quad mod\ 360^\circ$$

These two pieces of information constitute the core observations that can be obtained by the analog perception system, and are widely used in target localization and collision avoidance strategy modeling.

3.1.6 Dynamic Error Modeling and Observation Construction

To simulate the real sensor observation uncertainty, existing in the system design a set of dynamic error injection mechanism related to the distance. The error acts on the following variables:

The relative distance d_t error follows a normal distribution:

$$\varepsilon_d \sim \mathcal{N}(0,0.1)$$

The heading angle and azimuth angle errors vary according to the target distance, and the error range is as follows:

$$\varepsilon_\theta(d_t) = \begin{cases} [-0.5^\circ, 0.5^\circ], d_t \leq 100 \\ [-r(d_t), r(d_t)], 100 < d_t < 1500 \\ [-2.0^\circ, 2.0^\circ], d_t \geq 1500 \end{cases}$$

Where the error growth function is:

$$r(d_t) = 0.5 + \left(\frac{d_t - 100}{1400}\right) \cdot 1.5$$

The ship speed error is:

$$\varepsilon_v \sim \mathcal{U}(-0.5,0.5)$$

The above-mentioned errors respectively act on the fields such as "Observation Distance", " Observing ship 1 Heading ", " Observe boat 1 speed ", " Observe the relative azimuth ", etc., to form the simulated output of the perception system.

3.1.7 Time Interval Division and State Sampling

The total duration of the trajectory is set to 1200 seconds. Time sampling by generating more time period (interval), unless otherwise stipulated in the track events, the length of each time period in the [60,180] seconds between random sampling. If any motor behavior, keep its continuous period of time, the rest of the non-motor vehicle period were randomly divided, form the final time sampling point. The end of each time period is used as the state observation point to form the time series feature.

3.1.8 Segmentation Tags Generated

To achieve multi-stage prediction and combination strategy testing, each trajectory is randomly divided into 1 to n segments, and a unique "segment label" is assigned to each segment. The segmentation function executes multiple rounds of random trials under the constraint of a minimum segment length (e.g., 4 minutes, corresponding to 240 steps), and returns the optimal segmentation scheme that meets the conditions. The label ends up as an integer (1,2,... , n) tags are attached to each sample.

3.2 Model parameters

The parameter system recorded by the simulation program comprehensively covers the multi-dimensional characteristics of ship motion. Through meticulous parameter design, it achieves high-fidelity simulation of real sea conditions, as detailed in Table 1:

Table 1: Model Parameters Generated by The Simulation Program.

Parameter categories	Parameter names	Type	Description
Basic metadata	Run ID	True value	A number that uniquely identifies each simulation run
Base metadata	Time	True value	Timestamp of the trajectory point (in minutes)
Ship 1 (target)	Ship 1_X	True value	X-axis coordinates of boat 1 (true position)
	Boat 1_Y	True value	Y-axis coordinates of boat 1 (true position)
	Boat 1 heading	True value	True heading Angle of boat 1 (degrees, 0-360°)
	Boat 1 speed	True value	True speed of Boat 1 (in knots or meters per second)
	Boat 1 maneuver	Real value	Boat 1's maneuver type label
Boat 2 (reference boat)	Boat 2_X	True value	X-axis coordinates of Boat 2 (true position)
	Boat 2_Y	True value	Y-axis coordinates of Boat 2 (true position)
	Boat 2 heading	True value	True heading Angle of Boat 2 (degrees, 0-360°)
	Boat 2 speed	True value	True speed of Boat 2 (same units as above)
	Boat 2 Maneuver	Real value	Boat 2's Maneuver type label
Relative motion parameter	Actual distance	True value	The true straight-line distance between the two ships (in meters or nautical miles)
	Relative azimuth	True value	Boat 2's azimuth relative to Boat 1 (degrees, 0-360°)
Observations (with error)	Observation distance	Observations	The observed distance after injecting the distance error
	Observing ship 1 Heading	Observations	Ship after injecting heading error 1 Observe heading
	Observe boat 1 speed	Observations	Ship 1 observed velocity after injection of velocity errors
	Observe Boat 2 heading	Observations	Ship after injecting heading error 2 Observe heading
	Observe the relative azimuth	Observations	Observed relative azimuth Angle after injecting azimuth error
Segmentation and error parameters	Segment labels	Segment information	Track segment number (to distinguish between different voyage phases)
	Heading error (implied)	Error parameters	Deviation of course observations from true values (boat 1/ boat 2)
	Azimuth error (implied)	Error parameters	Deviation of the relative azimuth observation from the true value

3.2.1 Engineering Significance of Parameter Configuration

1) Multi-dimensional coupling modeling

Through the dynamic association of "course-speed-position" (for example, steering is accompanied by speed adjustment and position offset), it ensures that the generated data conforms to the kinematics of the ship, and avoids the physical irrationality of synthetic data.

2) Non-uniform sampling simulation

The different setting of the time interval in the maneuvering and non-maneuvering segments (see Section 3.1.7) directly corresponds to the high-frequency sampling strategy of the sensor when the target state changes dramatically, which enhances the fit between the data and the actual scene.

3) The authenticity of error mechanism

The range-dependent error model refers to the real sensor characteristics (e.g., radar ranging accuracy decreases with distance), which makes the simulation data more generalized and ensures the reliability of the model in real sea conditions.

3.2.2 Data Scale and Distribution

Sample size: A total of 5000 independent samples were generated, and each group contained 2 ships and trajectory data within 1200 seconds, with a total data volume of about 600 000 records.

Scenario coverage: It included steering maneuver, acceleration and deceleration maneuver, and pure direct flight scenarios. The error level was divided into short range (<500 meters), medium range (500-1500 meters), and long range (>1500 meters) according to the distance to ensure the diversity and balance of the training data.

Through the above parameter design, the simulation model realizes the multi-physics coupling modeling of the maritime target motion, provides training and testing data close to the real scene for the STC-BiLSTM-Attention model, and supports the verification of its adaptive solving ability in the non-uniform sampling environment.

4. Experimental data processing and analysis

Hold to verify the proposed STC BiLSTM - Attention model under non-uniform sampling data of sea targets forecast the effectiveness and superiority of calculating error, this paper designed a series of experiments, simulation data to construct, contrast scheme evaluation and module performance analysis, and many other aspects. The experiments are carried out from both qualitative and quantitative perspectives, and the performance of the model is comprehensively evaluated by combining visualization and numerical analysis.

4.1 Preprocessing of Simulation Data

In order to ensure the accuracy of the algorithm evaluation and the consistency of the experimental process, this paper conducts systematic data preprocessing on the original trajectory data, which mainly includes data reading, cycle and segment division, algorithm combination generation, input construction and other steps.

Firstly, multiple simulated or real ship trajectory data are read from the generated simulation data. The data format contains fields such as "run ID" and "segment label" to identify the period to which each record belongs and its position in the period. After reading, the data is sorted according to the run ID and the time field, and the index is reconstructed to ensure the consistency of the time series.

Then, the system partitions each run period (i.e., each complete navigation trajectory) according to its "segment label" field. Each cycle is further subdivided into several segments, each corresponding to a continuous navigation segment or maneuver behavior. On this basis, the preprocessing module constructs all possible combinations of algorithms. Given that the current cycle contains n segments and the number of trajectory estimation algorithms available to the system is m, the total number of combinations is. m^nIn this study, six different traditional single plotting algorithms have been incorporated into the model, so the number of combinations can reach hundreds.

In the data preparation stage, each trajectory needs to construct its input data. For the first segment in each combination, the system selects the first four data from the beginning of the segment as the initial input. For the non-first segment, according to the requirements of the selected algorithm, the latest 1 or 2 observations are extracted from the end of the previous segment and concatenated to the previous segment to ensure the continuity of the algorithm state. Especially, if some algorithms have strong inertia dependence (e.g., algorithms using sliding Windows or filters), the system will automatically provide them with longer historical context.

After completing the input construction, the system executes the specified algorithm function of each segment in turn for each combination, and records the meta-information such as running time, segment length, and the number of the algorithm used. Combinations that fail to run will be automatically skipped and the exception type will be recorded to ensure the robustness of the processing flow. The running results of all combinations are summarized and saved, including the complete trajectory estimation output file (which can be saved in batches) and the summary statistics file for each combination, which is convenient for subsequent algorithm comparison and performance analysis.

The design of the preprocessing flow ensures the consistency of algorithm evaluation and the scalability of high-throughput experiments, which is the core support module of the experimental system in this paper.

4.2 Model Validation

Two kinds of data sources are used to verify the model: one is the large-scale simulation data generated by parameter control and noise modeling, and the other is the measured ship sailing data. The simulation data are generated by the model in Section 3. Each round of simulation contains the trajectories of two ships within 1200 seconds, covering typical behaviors such as constant speed straight sailing, acceleration and deceleration, and left-right turning, and adding dynamic errors related to the target distance. A total of 5000 sets of samples were generated to ensure the diversity of different environments and behavior distributions.

In order to comprehensively evaluate the prediction performance of the fused STC-BiLSTM model under different calculation combination strategies, in this study, we designed an accuracy test mechanism based on the average ranking of the real value and the predicted value. Specific approach is to first data extracted from multiple simulation results, and for each operation within the ID label each combination of the real value and predictive value are calculated respectively the average. On this basis, all the combinations in each sailing cycle are sorted according to the average value of the real value and the average value of the predicted value. We will forecast the combination of the average ranked first as the operation model of optimization results, and further determine whether the combination is an average sort of real value first, if it is, argues that the predicted results are accurate. The overall prediction accuracy was calculated by counting the ratio of the number of accurate predictions to the total number of runs. This method can not only quantitative prediction effect under the different combination strategies, also have a certain robustness, suitable for complicated sea conditions and inhomogeneous observation model under the condition of optimizing analysis.

The same training-testing partition (80% training, 20% testing) was used for all models, and the input length and feature consistency were maintained. In the validation group, five sets of data were used for experimental average to avoid the contingency caused by initialization.

4.2.1 Model Comparison

In order to systematically evaluate the performance of STC-BiLSTM-Attention model under different architectures, this paper compares it with traditional and mainstream neural network models, including: Bidirectional Recurrent neural Network (BRNN), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), Bidirectional GRU (Bi-GRU), and basic LSTM model. All models used the same training set, feature input, hyperparameters and evaluation metrics. The experiment was repeated on five independent datasets, and the average accuracy was calculated.

The comparison results are shown in Table 2. The STC-BiLSTM-Attention model achieves the highest prediction accuracy in all five groups of data, of which group 4 reaches 93.36%, group 3 and group 5 also reach 91.03% and 91.87%, respectively. The average accuracy of STC-bilSTM-Attention is 89.75%, which is significantly better than all other comparison models, showing excellent time series modeling ability and generalization performance.

Among all comparison methods, the average accuracy of Bi-GRU is 75.12%, which is slightly higher than that of BRNN (74.38%) and CNN (72.96%), indicating that the introduction of bidirectional structure has a positive effect on improving the accuracy of time series prediction. The performance of GRU is relatively stable (71.11%), while the accuracy of the basic LSTM model is the lowest in the face of non-uniformly sampled data, indicating that it has obvious shortcomings in long-distance dependence and dynamic feature capture.

The comprehensive analysis shows that STC-BiLSTM-Attention can effectively capture short-time mutation and long-range dependence in complex ship maneuver behavior, adapt to non-uniform time structure, and has significant advantages in the prediction task of Marine target calculation error.

4.2.2 Ablation Experiment

In order to further analyze the performance contribution of each component module of STC-BiLSTM-Attention, this paper designs multiple sets of ablation experiments to gradually remove the key structural units and evaluate their impact on the overall prediction accuracy.

The experimental results are shown in Table 3. The average accuracy of the STC-BiLSTM-Attention model with the complete structure is 89.75%, ranking first among all groups. After removing STC, the accuracy of the BiLSTM+Attention model decreases to 81.96%, indicating that the convolution structure plays an important role in short-term mutation modeling. If further remove attention mechanism, retain only BiLSTM, its accurate rate fell to 75.98%, suggests that the key point of attention mechanism of heterogeneous data identification has played a positive role.

The average accuracy of the STC+LSTM model combined with STC and unidirectional LSTM is 73.14%, which is slightly better than that of TCN-bilSTM (74.42%), which uses TCN to replace STC, indicating that STC is more suitable for local feature modeling of maritime target data under non-causal structure. The accuracy of the basic LSTM model is only 53.63%, and it is as low as 34.38% in group 1, which highlights the serious performance degradation of the traditional model under non-uniformly sampled time series data.

In summary, the performance advantage of STC-bilSTM-attention does not come from a single module, but the collaborative modeling result of STC convolutional layer, bidirectional LSTM structure and self-attention mechanism. Short-term mutation characteristics of the structure can capture and global dependence, modeling and dynamic focusing on critical moment, to realize high precision error prediction under complex mobile scenarios.

4.3 Comparison Experiment with Traditional Single Solver Scheme

In order to further verify the effectiveness of STC-BiLSTM-Attention model in practical solving tasks, this paper compares it with traditional solving schemes such as Kalman filter [5] and manual single scheme drawing [4]. The experiment is carried out in four typical scenarios, covering the combination of uniform/non-uniform sampling and steady-state/high dynamic maneuverability. The evaluation index is the error rate (the proportion of deviation between the predicted position and the true position, where lower values indicate higher accuracy). The experimental results are shown in Table 4.

The experimental results are shown in Table 4. In scene 1 (uniform + steady state), the performance of the three traditional methods is close, and STC-BiLSTM-Attention has advantages but the gap is not large. However, in scenario 2 (non-uniform + steady state), the error of traditional methods increases significantly, while STC-BiLSTM-Attention remains below 7%, showing its strong robustness to non-uniform sampling structure.

In the more challenging scene 3 (uniform + high dynamic) and Scene 4 (non-uniform + high dynamic), the advantage of STC-BiLSTM-Attention is further expanded. Especially in scene 4, the error rate of STC-bilSTM-Attention is 8.52%, which is significantly improved compared with Kalman filter (21.36%) and manual single scheme plotting (27.84%). The results validate the mutations on STC module on the sensitivity of the response, BiLSTM modeling ability of long-term dependence and attention mechanism focusing effect of the synergy of critical moment.

4.4 Verification of Results

The results show that the STC-BiLSTM-Attention model proposed in this paper is superior to the comparison models in all indicators, especially in the identification ability of key mutations caused by non-uniform sampling. The introduced Spatio-temporal Convolutional Layer (SCT) significantly improves the response ability of the model to local short-term maneuvers, and the attention mechanism further enhances the attention to abnormal time slices, so as to maintain high prediction accuracy and stability in multiple scenarios.

Table 2: Comparison of Models.

Model names	Prediction accuracy -Group 1	Prediction Accuracy - Group 2	Prediction Accuracy - Group 3	Prediction Accuracy - Group 4	Prediction Accuracy - Group 5	Average Accuracy
STC-BiLSTM-Attention	82.07%	88.42%	91.03%	93.36%	91.87%	89.75%
BRNN	71.24%	75.02%	78.11%	74.88%	72.65%	74.38%
CNN	69.33%	71.85%	73.09%	76.12%	74.41%	72.96%
GRU	67.82%	69.74%	72.16%	73.89%	71.93%	71.11%
Bi-GRU	70.03%	74.15%	76.00%	78.28%	77.14%	75.12%

Table 3: Ablation Experiments.

Model Name	Prediction Accuracy - Group 1	Prediction Accuracy - Group 2	Prediction Accuracy - Group 3	Prediction accuracy -Group 4	Prediction Accuracy - Group 5	Average Accuracy
STC-BiLSTM-Attention	82.07%	88.42%	91.03%	93.36%	91.87%	89.75%
BiLSTM + Attention	77.12%	80.96%	82.71%	85.60%	83.43%	81.96%
BiLSTM	71.33%	74.82%	77.29%	79.54%	76.90%	75.98%
STC + LSTM	69.50%	72.01%	74.26%	75.88%	74.05%	73.14%
TCN-BiLSTM	70.46%	73.64%	75.19%	77.81%	75.00%	74.42%
LSTM	34.38%	48.72%	56.83%	63.35%	62.87%	53.63%

Table 4: Comparison of Error Rates Between Traditional Methods and The Proposed Model in Different Scenarios.

	Kalman filter	Manual single scheme plotting	STC-BiLSTM-Attention
Scenario 1: Uniform + steady state	5.23%	8.52%	4.15%
Scenario 2: Non-uniform + steady state	12.47%	18.79%	6.89%
Scenario 3: Uniform + high dynamic	9.85%	14.63%	6.27%
Scenario 4: Non-uniform + high dynamic	21.36%	27.84%	8.52%

5. Conclusion Theory

This paper aims at the practical problems of time series data of maritime targets, such as non-uniform sampling, dynamic maneuvering mutation and noise interference. This paper proposes a hybrid deep regression model combining Spatio-Temporal Convolution (STC), bidirectional LSTM (BiLSTM) and Attention mechanism (STC-bilSTM-Attention). The spatio-temporal convolution layer enhances the ability of local short-term feature extraction, the bidirectional LSTM realizes long-term dependence modeling, and the attention mechanism focuses on key time point information to achieve high-precision modeling and prediction of calculation error under complex navigation behavior.

The experiments are evaluated on large-scale simulation data and some measured data. The results show that the proposed model is significantly better than traditional CNN, GRU, LSTM and other models in terms of prediction accuracy, with an average increase of more than 10%. At the same time, ablation experiments further verify the importance of the synergistic effect of the three modules in improving the performance of the model. Among them, the SCT module has a particularly prominent effect on mutation identification, and the self-attention mechanism has a particularly obvious adaptability to non-uniform sampling.

In summary, the STC-BiLSTM-Attention model shows superior robustness and generalization ability in non-uniformly sampled dynamic target solving tasks, which has a wide range of engineering application potential. Future research can further combine multi-source heterogeneous data (such as AIS, radar, visual information) and graph neural network and other emerging structures to expand the adaptability and practicability of the model, and provide technical support for building a more intelligent comprehensive perception and prediction system for maritime targets.

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