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Convolutional Bidirectional Long Short-Term Memory-based Dynamic Noise Adaptive Distributed Collaborative Maneuvering Target Tracking

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A distributed cooperative target tracking algorithm based on a convolutional bidirectional long short-term memory (ConvBiLSTM) neural network is proposed to address the nonnegligible and changing observation noise caused by previous passive maneuvering target tracking. The algorithm improves the time difference of arrival/frequency difference of arrival (TDOA/FDOA) measurement accuracy by utilizing the ConvBiLSTM neural network to correct the sensor observations to adapt to the dynamically changing observation environment, as well as combining with the weighted two-step least squares method to reduce the initial estimation error. The experimental results show that the algorithm can be used to estimate the target position and velocity more accurately in maneuvering target tracking environments with large observation errors, and at the same time, improves the stability of target tracking.

1. Introduction

In traditional passive moving target tracking, the nonnegligible and time-varying nature of observation noise represents the core bottleneck constraining tracking accuracy. Its root causes can be attributed to three aspects. First is the inherent characteristic of sensor hardware: the receivers used to collect time difference of arrival/frequency difference of arrival (TDOA/FDOA) information exhibit time delay errors and frequency drift. Such hardware errors directly accumulate in the observation data and cannot be fully eliminated through algorithms. The second is interference from complex environments. During propagation, signals are affected by multipath reflections, electromagnetic interference, and other factors. The intensity and

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distribution of these interferences dynamically fluctuate with target position, causing unstable observation noise. The third aspect is the indirect effect of target maneuvering. When a target accelerates, turns, or performs other maneuvers, its relative motion with respect to the observation station changes. This induces Doppler shifts and dynamic adjustments to the signal propagation path length, altering the noise characteristics of the TDOA/FDOA observations. Theoretically, this noise characteristic cannot be ignored: The core of passive maneuvering target tracking involves estimating target states through observation inversion. The presence of observation noise directly amplifies state estimation errors. Ignoring noise or assuming constant noise levels causes estimation results to deviate from true target states, potentially compromising tracking validity. This limitation becomes particularly pronounced when noise dynamically varies with environmental conditions and timing sequences, highlighting the inadequacy of traditional fixed-noise models. Consequently, a tailored noise adaptation mechanism must be designed.

Noisy sensor observations remain a central challenge in the passive tracking of maneuvering emitters. In prior studies, either the observation model or the estimator has mainly been improved. Zhou *et al.*(1) developed a partially constrained weighted least squares (WLS) method for TDOA/FDOA localization and reported accuracy gains; however, its performance degrades when the observation noise statistics are unknown or poorly estimated. Li and Zhu(2) introduced an extended Kalman filter that corrects the ranging model using received-signal-strength information, but the intrinsic instability of received signal strength indicator (RSSI)-based ranging can propagate large errors into the tracker. Li *et al.*(3) used particle swarm optimization to adaptively tune the covariance of the extended Kalman filter, aiming to improve accuracy; in highly dynamic settings, however, rapid fluctuations of the fitness landscape can hinder convergence and robustness for noisy, nonlinear motion models. Deng *et al.*(4) proposed a two-step WLS (TSWLS) algebraic solution that jointly exploits DOA, TDOA, and FDOA by pseudo-linearizing the nonlinear equations via auxiliary parameters, yielding refined position-and-velocity estimates; the associated algebraic augmentation and repeated matrix operations, however, can introduce nonnegligible computational overhead and latency in real-time tracking.

To clearly highlight the innovation of this research, we systematically compare the traditional passive moving target tracking method with the distributed collaborative target tracking algorithm proposed in this paper, using a convolutional bidirectional long short-term memory (ConvBiLSTM) neural network. The comparison focuses on core principles, noise handling capabilities, and positioning logic. In traditional methods, the TSWLS approach achieves localization by linearizing nonlinear TDOA/FDOA equations. However, it relies on a fixed-noise model to predefine the weight matrix, making it unsuitable for dynamically varying observation noise in maneuvering target tracking. This mismatch between weights and noise characteristics often leads to increased initial estimation errors. Extended Kalman filtering achieves tracking through recursive target state updates, yet requires the linearization of nonlinear models using the Jacobian matrix. This approach not only introduces truncation errors but also exhibits sensitivity to non-Gaussian observation noise, resulting in significantly degraded tracking stability during high-velocity target maneuvers. Although particle swarm optimization is applied to extend the covariance matrix of the extended Kalman filter, it struggles to cope with the rapid changes in fitness function in dynamic environments. Tracking performance is prone to degradation under scenarios involving spatially heterogeneous or fluctuating temporal noise.[5–7]

In contrast, the core innovation of our work lies in constructing an integrated framework combining deep learning correction, dynamic weighted estimation, and distributed collaborative localization: First, we innovatively propose the ConvBiLSTM neural network. By utilizing convolutional layers to extract spatial distribution features from multisensor observations, it effectively suppresses sudden local spatial heterogeneous noise. Simultaneously, it leverages the bidirectional temporal modeling capability of BiLSTM to precisely track noise evolution trends over time, enabling the real-time dynamic correction of TDOA/FDOA observations. This provides more reliable observation inputs for subsequent positioning. This design addresses the gap in traditional methods that solely rely on signal processing algorithms without incorporating observation data preprocessing. Second, building upon ConvBiLSTM-corrected observations, advanced signal processing algorithms such as full-squared WLS are introduced. By dynamically updating the weight matrix and re-estimating the noise covariance based on corrected observations, initial estimation errors are reduced, overcoming the limitation of traditional TSWLS static weights failing to adapt to time-varying the noise. Finally, leveraging a distributed collaborative architecture to integrate multisensor measurement data, it combines the advantages of TDOA/FDOA joint positioning models to fuse time-of-arrival and frequency-of-arrival measurement techniques, further enhancing target positioning accuracy and reliability. Traditional approaches often rely on isolated single sensors or positioning techniques, but fail to achieve deep integration among sensor measurements, deep learning corrections, and signal processing optimizations. The proposed method, through the aforementioned design, not only suppresses dynamic noise and enhances observation reliability but also provides a more robust logical foundation for target state estimation in complex maneuvering scenarios.

2. Positioning Model

The TDOA/FDOA joint positioning model employs two technologies: time difference of arrival and frequency difference of arrival. The objective is to enhance the accuracy and robustness of target positioning. This model utilizes the time and frequency differences of a signal source arriving at different receiving stations to construct an optimization problem for target position and velocity. This results in more accurate estimates of target position and velocity.[8–10]

TDOA technology is based on measuring the time difference of a signal source arriving at different receiving stations and constructing hyperbolas or hyperboloids to estimate the target position. In contrast, FDOA technology utilizes Doppler shift to estimate target velocity, thereby further enhancing positioning accuracy. By combining the information from TDOA and FDOA, the TDOA/FDOA joint positioning model can achieve more precise target positioning in complex environments.

The main focus of this study is the three-dimensional positioning scenario, where M mobile receivers are randomly deployed as TDOA/FDOA joint positioning observation stations for the target source S_T. The position information of the mobile receivers is denoted as $S_i(x_i, y_i, z_i)$ and the velocity information as $\dot{S}_i(\dot{x}_i, \dot{y}_i, \dot{z}_i)$. In the typical scenario, the first receiver is chosen as the reference, referred to as receiver 1, with its position denoted as $S_1(x_1, y_1, z_1)$ and its velocity as $\dot{S}_1(\dot{x}_1, \dot{y}_1, \dot{z}_1)$. The position and velocity of the mobile target radiation source are assumed to be $S_T(x, y, z)$ and $\dot{S}_T(\dot{x}, \dot{y}, \dot{z})$, respectively. To determine the position and velocity information of the mobile target radiation source, at least four receivers are required to simultaneously generate three TDOA/FDOA parameters. Therefore, the problems of passive localization with time and frequency differences discussed in this paper are mainly in scenarios where the number of receivers is greater than 4.

We consider passive localization scenarios in which at least four receivers operate at the same time. This configuration provides three independent measurements of TDOA and FDOA, which together allow reliable estimations of the position and velocity of a moving emitter. When more than four receivers are available, the additional observations strengthen the constraints and generally improve the accuracy and robustness. Figure 1 illustrates a typical deployment in which several spatially separated receivers collect the time and frequency difference measurements that are used by the localization model and the solver. r_i^o is defined as the true distance between the moving target radiant source and the I-th receiver.

$$r_i^o = \left\| S_T, S_i \right\| = \sqrt{\left(S_T - S_i\right)^T \left(S_T - S_i\right)} \tag{1}$$

The positions of different receivers relative to the moving target radiation source are not the same, resulting in different time delays in the signals received by different receivers. This also reflects the difference in distance between the receivers and the moving target radiation source, which can be expressed as

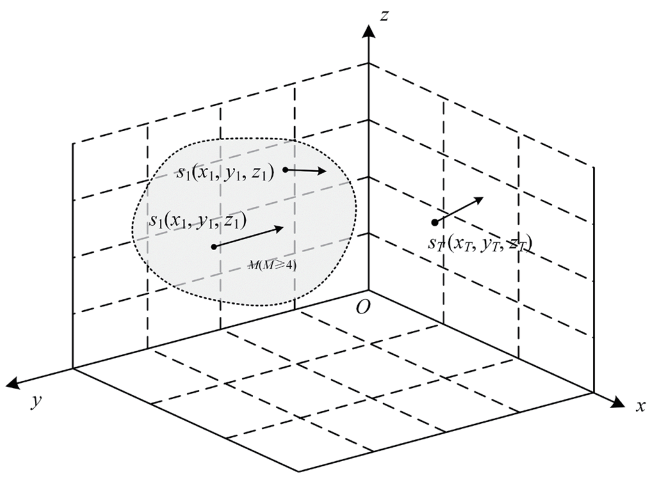

Fig. 1. Joint positioning model.

$$r_{i1}{}^{o} = r_i^{o} - r_1^{o} = c\Delta t_{i1}\,. \tag{2}$$

Here, $r_{i1}{}^{o}$ represents the distance difference between the i-th receiver and the reference receiver (receiver 1), and c represents the propagation speed of the electromagnetic wave signal.

After a simple mathematical transformation from Eqs. (1) and (2), the following TDOA equation can be obtained:

$$2\left(S_i - S_1\right)^T S_T + 2r_{i1}^{o} r_1^{0} = S_i^T S_i - S_1^T S_1 - r_{i1}^{o^2} \; i = 1,2,...,M. \tag{3}$$

The TDOA equation can only calculate the position information of the mobile target radiation source but cannot estimate the target speed. When there is relative motion between the mobile target radiation source and the base station, the base station will measure the Doppler frequency change, and by using the resulting frequency difference, it will be able to estimate the moving speed of the target, while simultaneously improving the estimation of the position of the mobile target radiation source.

Similarly, for the arrival frequency, the FDOA calculation formula can be derived using the same mathematical method, as shown below.

$$\begin{aligned} &\left(S_i^{v} - S_1^{v}\right) S_T + \left(S_i - S_1\right) S_T^{v} + r_{i1}^{v^o} r_1^{o} + r_{i1}^{o} r_1^{v^o} = \\ &S_1^{vT} S_i - S_1^{vT} S_1 - r_{i1}^{v^o} r_{i1}^{0} \quad i = 1,2,...,M \end{aligned} \tag{4}$$

First, the variable to be measured $x = [S_T \; r_1^{0} \; S_T^{v} \; r_i^{v^o}]$ is defined, which includes the position and velocity of the mobile target radiation source and the true distance and Doppler frequency change between reference base station No. 1 and the mobile target radiation source, which can be obtained by collapsing the TDOA and FDOA equations by association.

$$G^{o} x = h^{o} \tag{5}$$

Here, in G^o and h^o, r_i^{o} and $r_i^{v^o}$ are both cases where there is noise interference in the actual scenario, and if we consider the impact generated by the noise interference, then

$$G\,x = h + \varepsilon\,, \tag{6}$$

where ε is the error matrix associated with the TDOA/FDOA observation noise. At this point, the cost function is expressed as

$$J = \left(G\,x - h\right)^T W \left(G\,x - h\right). \tag{7}$$

This transforms the problem of locating a moving target radiation source into that of solving the unknown variable x subject to minimizing the cost function *J*.

3. Observation Correction Method Based on ConvBiLSTM Neural Network

We aim to correct TDOA/FDOA values when environmental samples suffer from severe noise interference and thereby achieve superior correction performance under high signal-to-noise ratios. To this end, we combine data processing with deep learning models to correct TDOA/FDOA values. In Fig. 2, we show the overall correction framework of this method, which primarily comprises three modules: data preprocessing, TDOA/FDOA correction, and prediction performance evaluation modules. The data preprocessing module cleans, transforms, and normalizes raw data to enhance its quality and usability. The TDOA/FDOA correction module corrects time and frequency differences within the positioning system to improve positioning accuracy and precision. It can correct measurement data from observation stations in accordance with actual conditions, eliminating errors and noise to enhance the positioning system's performance. The prediction performance evaluation module assesses and validates established prediction models to determine their accuracy and reliability. This helps users understand the model's predictive capabilities and facilitates corresponding adjustments and improvements.

3.1 ConvBiLSTM neural network

The ConvBiLSTM neural network is an advanced deep learning architecture that combines the strengths of both convolutional neural networks (CNNs) and BiLSTM networks. CNNs are particularly adept at extracting spatial features from data, while BiLSTMs are highly effective at capturing long-term dependences in sequential data. The combination of these two components enables the ConvBiLSTM to process both feature and sequential data simultaneously, providing a robust solution for a range of complex tasks. The schematic diagram of the ConvBiLSTM neural network is shown in Fig. 3.

The core of the longitudinal feature extraction module is the CNN, a deep learning model that is particularly adept at capturing spatial and spectral features. In the TDOA/FDOA correction model, the CNN performs convolutional operations on the received signals, extracting crucial features that are essential for target localization. These include signal time-frequency characteristics and spatial distribution features. These features provide important informational support for subsequent target localization.

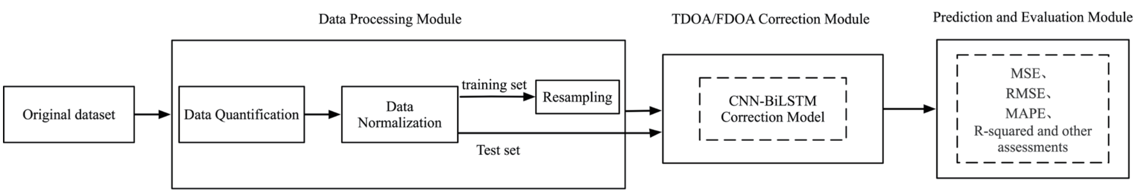

Fig. 2. TDOA/FDOA correction framework.

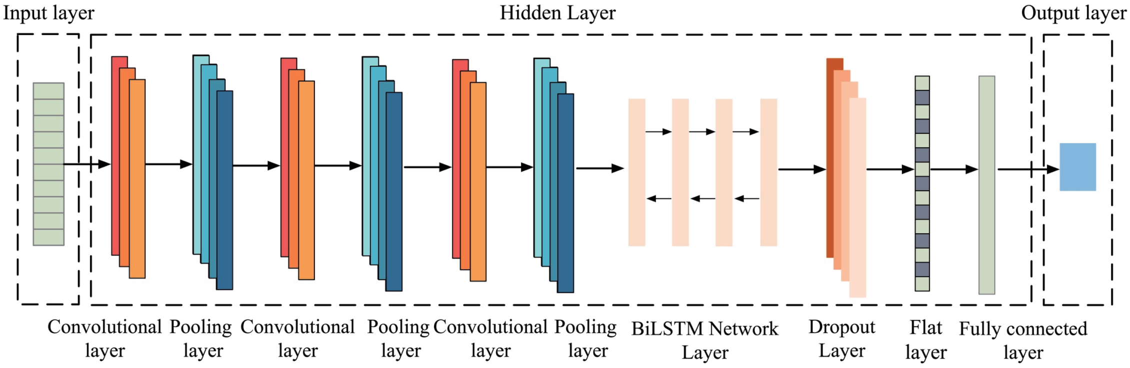

Fig. 3. (Color online) Schematic diagram of ConvBiLSTM neural network.

The role of the CNN in this model extends beyond feature extraction. It also plays a role in the modeling of spatial information. Given that target localization involves signals received from multiple observation stations, the spatial information in these signals is crucial for precise positioning. The CNN learns the spatial relationships between different observation stations through convolutional operations, effectively modeling the spatial information. This modeling helps to reduce errors in TDOA/FDOA estimation, thereby enhancing the accuracy and robustness of target localization. In summary, the CNN plays a pivotal role in the longitudinal feature extraction module. It not only extracts rich signal features but also effectively models spatial information, collectively improving the performance of the TDOA/FDOA correction model. The structural diagram of the CNN is shown in Fig. 4.

The core of horizontal feature extraction is BiLSTM, which plays a key role in temporal modeling in the model. BiLSTM is unique in its ability to simultaneously process forward and backward information in the input sequence, thereby capturing contextual information more comprehensively. It consists of two independent LSTM layers, one focusing on processing forward information and the other on analyzing backward information. Each LSTM layer has independent hidden states and memory units, which can capture long-term dependences in the sequence, enabling the effective modeling of sequential data. This bidirectional processing approach enables BiLSTM to have advantages in understanding and analyzing sequential data, providing strong support for improving the performance of the overall model.

In Fig. 5, x_t represents the input at time t, h_t represents the hidden layer output at time t, C_t represents the memory cell at time t, C_t represents the temporary memory cell, ⊕ represents elementwise addition, ⊗ represents elementwise multiplication, and C_t contains information determined by the forget gate.

BiLSTM also plays an important role in information fusion. In the TDOA/FDOA correction model, multisource information from different observation stations needs to be effectively integrated to improve the accuracy of positioning and correction. BiLSTM, with its bidirectional structure, can simultaneously consider past and future information, thereby better integrating information from different observation stations and improving the overall performance of the model. The structure of the BiLSTM network is shown in Fig. 6.

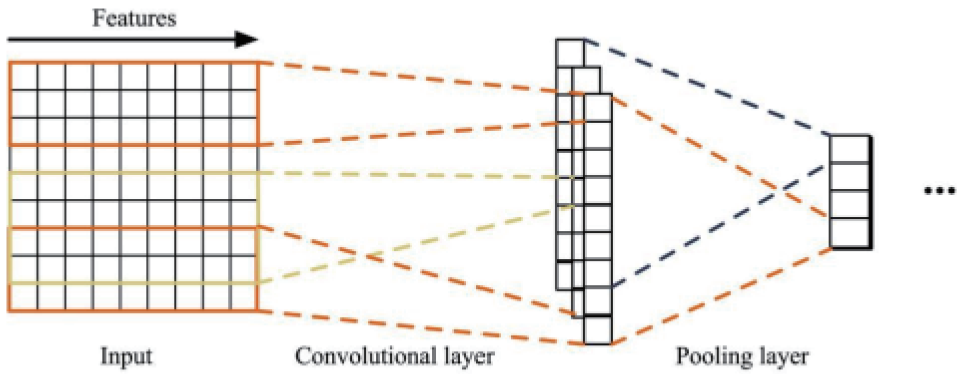

Fig. 4. (Color online) CNN structure.

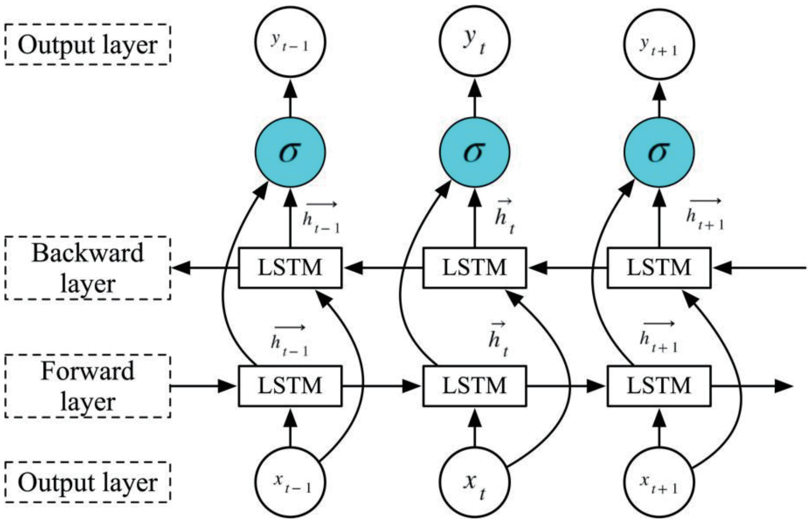

Fig. 5. (Color online) LSTM cell structure.

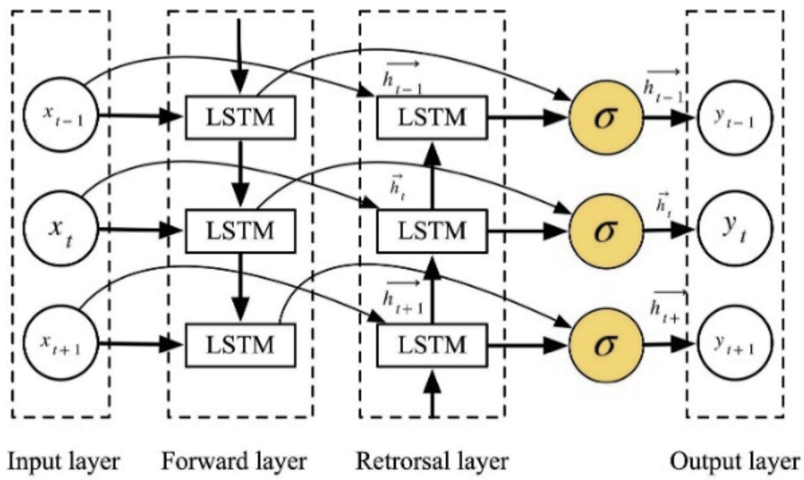

Fig. 6. (Color online) BiLSTM network structure.

BiLSTM's other key role in the model is temporal modeling. The TDOA/FDOA correction model needs to model the timing information of the input signal in order to accurately calculate the time or frequency difference. BiLSTM, as a neural network structure suitable for time series data processing, can effectively learn and capture the timing patterns in the signal, thus providing accurate timing modeling capabilities for the correction model.(11,12)

3.2 Correction of TDOAFDOA values using ConvBiLSTM neural network

In traditional passive moving target tracking, the nonnegligible and time-varying nature of observation noise represents the core bottleneck constraining tracking accuracy. Its root causes can be attributed to three aspects. The first is the inherent characteristic of sensor hardware: receivers used to collect TDOA/FDOA information exhibit time delay errors and frequency drift. Such hardware errors directly accumulate in the observation data and cannot be fully eliminated through algorithms. The second is interference from complex environments. During propagation, signals are affected by multipath reflections, electromagnetic interference, and other factors. The intensity and distribution of these interferences dynamically fluctuate with target position, causing unstable observation noise. The third aspect is the indirect effect of target maneuvering. When a target accelerates, turns, or performs other maneuvers, its relative motion with respect to the observation station changes. This induces Doppler shifts and dynamic adjustments of the signal propagation path length, consequently altering the noise characteristics of TDOA/FDOA observations. Theoretically, this noise characteristic cannot be ignored; the core of passive maneuvering target tracking involves estimating the target state through observation inversion. The presence of observation noise directly amplifies state estimation errors. Neglecting noise or assuming it to be constant leads to estimation results deviating from the true target state, potentially even causing loss of tracking effectiveness. The limitations of traditional fixed-noise models become particularly pronounced when noise dynamically varies with environment and timing. Therefore, a targeted approach is essential. The hardware used for TDOA/FDOA observation data acquisition in this study is a mobile receiver adaptable to RF or acoustic signal reception. Specific deployment and observation procedures are based on the "multistation collaborative positioning" framework defined in Sect. 2. We employ a mobile receiver for TDOA/FDOA observation data acquisition, adaptable for both RF and acoustic signal reception. The deployment and observation workflow adhere to the multistation collaborative positioning framework defined in the positioning model. Multiple mobile observation stations are deployed, with one designated as the reference station and the remainder as nonreference stations. All stations must maintain time synchronization to ensure the accuracy of TDOA and FDOA measurements. During observations, each station receives signals radiated by the target in real time. The reference station and nonreference stations respectively record signal arrival times and frequencies. By calculating the time and frequency differences between nonreference stations and the reference station, raw TDOA and FDOA observation data are obtained. On the basis of these sensor observations, ConvBiLSTM performs observation correction through four steps.

Step 1: Raw observations are preprocessed into an input dimension of "time steps × number of stations × 2", where the number 2 corresponds to TDOA and FDOA observations. Normalization eliminates numerical scale differences between the two observation types.

Step 2: Spatial features are extracted via a convolutional module. Convolution kernels capture the spatial distribution patterns of observation data across different stations, distinguishing useful signals from spatially heterogeneous noise. Batch normalization, activation functions, and pooling layers further optimize feature representation and reduce data dimensions.

Step 3: Temporal modeling is performed via a bidirectional long short-term memory module. The forward memory layer learns future evolution trends of observation noise, while the backward memory layer traces historical noise patterns. A gating mechanism filters temporal noise.

Step 4: Corrected TDOA/FDOA observations are output through a fully connected layer, providing more reliable input data for subsequent positioning algorithms.

4. TDOA/FDOA Localization Algorithm Based on Improved TSWLS (ImTSWLS) Method

WLS demonstrates significant advantages in passive moving target TDOA/FDOA positioning and tracking. Its core strengths lie in adaptability to observation data characteristics and enhanced estimation accuracy. First, unlike ordinary least squares, which assumes uniform error across all observations, WLS quantifies the reliability of different observations through a weighting matrix. Then, higher weights are assigned to observations with lower noise and higher precision while the interference of noisy, low-reliability observations on estimation results is reduced. This fundamentally enhances the handling capability for nonuniform error observations, making it particularly well suited to the practical scenario in TDOA/FDOA positioning, where "observation errors vary across different stations and observation types". Second, the ImTSWLS further enhances this advantage by dynamically updating the weight matrix and re-estimating noise covariance based on ConvBiLSTM-corrected observations. This enables weights to be adapted in real time to the time-varying noise characteristics of moving target tracking, addressing the limitations of traditional WLS methods with fixed weights that struggle with dynamic noise and often lead to reduced estimation accuracy. Moreover, WLS exhibits strong multidimensional observation fusion capabilities, effectively integrating diverse observation types such as TDOA and FDOA. By adjusting weights to balance contributions from both observation types, it fully leverages TDOA's strengths in position estimation and FDOA's advantages in velocity estimation, providing more comprehensive information support for joint positioning. Finally, this method integrates efficiently with iterative optimization logic. For instance, the ImTSWLS approach in this study employs a two-step iterative solution, using WLS as the core to achieve gradual optimization from coarse to fine estimation. This effectively reduces errors in solving nonlinear equations during TDOA/FDOA positioning, providing a reliable algorithmic foundation for the precise estimation of target position and velocity in complex maneuvering scenarios.(13)

To avoid lengthy derivations, the main text presents only the key expressions for the solution. On the basis of the observation model described by Eqs. (3) and (4) and the weighted cost of Eqs. (6) and (7), we linearize and employ WLS/Gauss–Newton iteration: the initial solution is provided by the standard model. Subsequently, the covariance matrix R is reconstructed using observation corrections and uncertainty provided by ConvBiLSTM, and the weight matrix is updated to achieve two-step weighted convergence. Incremental solutions and update rules are detailed in Eqs. (9)–(13).

Therefore, the WLS estimate for X_2 is

$$x_2 = \left(G_2^T W_2 G_2\right)^{-1} G_2^T W_2 G_2 \tag{9}$$

$$B_2 = \begin{bmatrix} I & 0 & O & 0 \\ S_T^T & r_1 & 0 & 0 \\ O & 0 & I & 0 \\ S_T^{vT} & r_1 & S_T^T & r_1 \end{bmatrix}. \tag{10}$$

The estimated position and velocity of the moving target radiation source at this time are

$$\begin{aligned} S_T &= U\left[\sqrt{x_2(1)}, \sqrt{x_2(2)}, \sqrt{x_2(3)}\right]^T + S_1 \\ S_T^v &= U\left[\frac{x_2(4)}{\sqrt{x_2(1)}}, \frac{x_2(5)}{\sqrt{x_2(2)}}, \frac{x_2(6)}{\sqrt{x_2(3)}}\right]^T + S_1^T \end{aligned} \tag{11}$$

$$U = diag\left[\operatorname{sgn}\left(x_u - s_1\right)\right] \tag{12}$$

$$x_u = \left[x(1) \quad x(2) \quad x(3)\right]^T. \tag{13}$$

In summary, the best estimate of the observed target's velocity and position can be achieved by iteratively calculating the estimated values from the first and second steps until the calculation error resulting from the two-step estimation falls below the predefined threshold or the algorithm reaches the preset maximum number of iterations. This approach ensures the accuracy and reliability of the estimated results.

The core logic of this method for achieving precise position and velocity estimations of complex maneuvering targets lies in a three-tiered collaborative approach: "Observation Correction–Dynamic Weighting–Iterative Optimization". The first tier involves the precision processing of observation data, where the ConvBiLSTM neural network corrects raw TDOA/FDOA observations; the convolutional layer extracts spatial features from multistation data, effectively suppressing localized, sudden spatial heterogeneous noise and enhancing the spatial consistency of observation data. The bidirectional LSTM layer employs two-way temporal modeling to capture observation noise trends over time, filtering out the temporal noise interference caused by target maneuvers. This process makes the corrected observation data more closely resemble the true signal characteristics. The second stage involves the dynamic adaptation of the weight matrix. On the basis of the corrected observations, the noise covariance matrix is re-estimated. A dynamic weight matrix is then constructed following the principle that "weights are inversely proportional to noise covariance. This design assigns higher weights to high-confidence observations in the least squares solution while appropriately suppressing the effect of low-confidence observations. This reduces initial estimation errors, laying the foundation for precise positioning. The third level involves iterative error approximation optimization, in which gradual refinement of estimates is achieved through a two-step iteration: First, a coarse estimate of target position and velocity is computed using the dynamic weight matrix. Second, a new linear equation is constructed in accordance with the mathematical relationship between the coarse estimate and auxiliary variables, followed by a WLS solution for fine estimation. Through multiple iterations, the estimation results gradually converge toward the optimal solution, ultimately achieving the precise estimation of the target state. Furthermore, ConvBiLSTM's noise suppression capability enables the noise intensity of corrected observations to decrease progressively with each iteration. This further ensures the stability of weight matrix updates and drives the entire system toward convergence to the optimal estimate.

5. Simulation Experiment and Analysis

To further verify the noise suppression ability of the algorithm, simulation experiments were conducted under Gaussian white noise and non-Gaussian white noise. Gaussian white noise is output 1 and non-Gaussian white noise is output 2. CNN, CNN BiLSTM, and CNN BiLSTM Attention were trained for experimental simulation. For the performance evaluation of the proposed prediction model, mean absolute error (*MAE*), root mean square error (*RMSE*), mean absolute percentage error (*MAPE*), and the coefficient of determination were used as evaluation indicators to measure the prediction effect.(14,15) The specific calculation process is as follows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - p_i\right| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - p_i\right)^2} \tag{15}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - p_i}{y_i}\right| \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{17}$$

The simulation results for Output 1 and Output 2 in Fig. 7 show that the evaluation metrics of *MAE*, *RMSE*, and *MAPE* for the proposed improved prediction method are all lower than those of the CNN model. This indicates that the prediction accuracy of the proposed model is higher than those of the other two algorithms. In addition, the parameter value for Output 1 is 0.978, whereas that for Output 2 is 0.986. The parameter is primarily used to assess the degree of fit of the model, with values closer to 1 indicating higher model quality. Therefore, this confirms that the proposed algorithm outperforms other algorithms in terms of prediction accuracy and model quality.

5.1 Routine testing

To verify the localization accuracy and robustness of the algorithm presented in this paper, Monte Carlo simulation experiments were performed. To quantify the difference in localization performance between different algorithms, we selected three representative algorithms for comparative analysis: the traditional TSWLS algorithm, its decentralized variant (DeTSWLS) that adapts to distributed scenarios, and the proposed ConvBiLSTM-based algorithm. Among them, DeTSWLS is a distributed implementation of the TSWLS framework, which is consistent with the distributed collaborative positioning background of this study and thus was selected as one of the comparative baselines. We used the *RMSE* of the estimated target position as an indicator of localization accuracy. *RMSE* is obtained by calculating the square root of the average of the squares of the differences between the estimated value and the true value, which

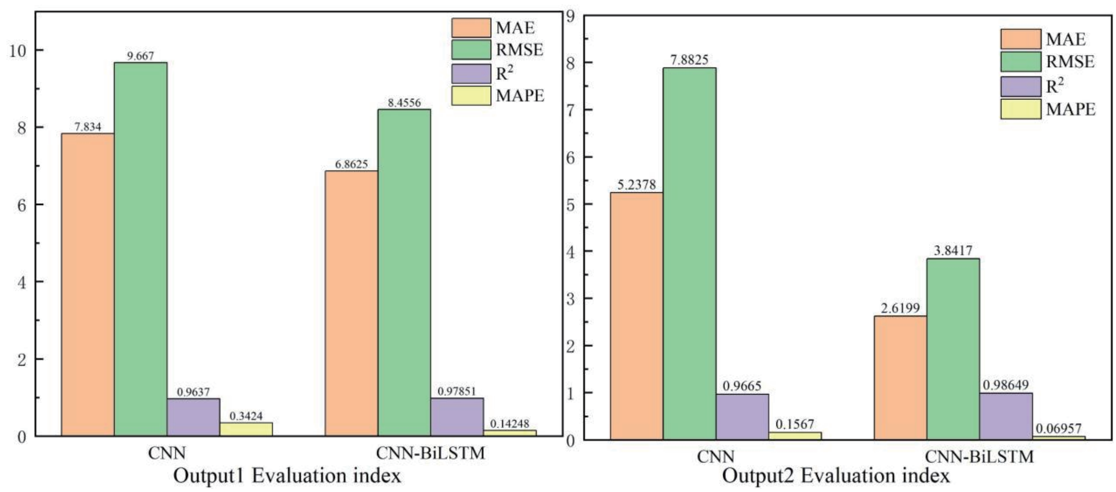

Fig. 7. (Color online) Prediction results for different models.

can effectively reflect the localization accuracy and stability of the algorithm. Through Monte Carlo simulation experiments, we can simulate different noise environments and target motion trajectories to comprehensively evaluate the performance of the algorithm proposed in this paper. The formulas are as follows.

$$RMSE\left(S_T\right)=\sqrt{\frac{1}{N}*\sum_{i=1}^{N}\left\|\hat{S}_T-S_T^o\right\|^2} \tag{18}$$

$$RMSE\left(S_T^v\right)=\sqrt{\frac{1}{N}*\sum_{i=1}^{N}\left\|\hat{S}_T^v-S_T^{v^o}\right\|^2} \tag{19}$$

The performance of the ImTSWLS positioning algorithm was validated through simulation experiments with the TDOA/FDOA correction model for convolutional long-short-term memory neural networks, and the results were compared with those of several other models. The simulation settings were as follows: S_T = [285, 325, 275], the position and velocity of the moving target radiation source were set to S_T^v = [−20, 15, 40], and five mobile observation stations were used to monitor the radiation source. The observation stations were distributed within a position range of −100 to 500 m and a velocity range of −30 to 30 m/s, with noise variance set between −20 and 20 dB. The parameter settings of the observation stations are detailed in Table 1.

Since the measurement errors of TDOA and FDOA are independent of each other, for comparison with other models, it is assumed that the measurement error matrix of TDOA is Q, and the measurement error matrix of FDOA is 0.1Q, where the expression of Q is

$$Q=\sigma^2\begin{bmatrix}1 & 0.5 & \cdots & 0.5\\ 0.5 & \ddots & 0.5 & \vdots\\ \vdots & \ddots & \ddots & 0.5\\ 0.5 & \cdots & 0.5 & 1\end{bmatrix}. \tag{20}$$

To simulate the distance measurements of observation stations with noise, we add Gaussian white noise with zero mean and variance σ_l^2 to the true value of the observation station distance. In the simulation experiment, we set σ_l to 0.01 m. Similarly, to simulate the time difference measurements with noise, we add Gaussian white noise with zero mean and variance σ_l^2 to the true value of the time difference t_i^{1o}. In the simulation experiment, we set σ_l to 1 ns. The

Table 1
Mobile observation station position and velocity parameters.

Station number	Station position $x/y/z$ (m)			Station velocity $x/y/z$ (m/s)		
1	300	100	150	30	−20	20
2	400	150	100	−30	10	20
3	300	500	200	10	−20	10
4	350	200	100	10	20	30
5	−100	−100	−100	−20	20	20

introduction of these noises helps to more closely resemble the actual situation, thereby evaluating the performance of the algorithm in the presence of noise interference.

From the results in Fig. 8, we can see that after detailed data analysis, the use of ConvBiLSTM neural networks to improve the TDOA ranging model has achieved significant results in error control. Compared with traditional TDOA ranging models, the improved model shows clear advantages in both the weighted minimum two-part estimation error and the weighted minimum estimation error. Through simulation verification, as the position error of the observation station gradually increases, the algorithm proposed in this paper shows excellent positioning accuracy stability in the face of the position error of the observation station. Even if there is uncertainty in the position of the observation station, the algorithm can still accurately calculate the target position. This is mainly because the algorithm effectively corrects the precise distance information between the observation stations, which significantly reduces the effect of the position error.

By using the ConvBiLSTM neural network to correct the measurement information, the positioning accuracy of the algorithm in this paper has been significantly improved. In particular, the more accurate the observation information is, the more significant the improvement in the positioning accuracy of the algorithm in this paper. However, as the observation error of the observation station gradually increases, the improvement in positioning accuracy brought about by correcting the measurement information gradually weakens. When the observation error of the observation station increases to a certain extent, the correction of the measurement information by the ConvBiLSTM neural network limits the improvement in positioning accuracy. Nevertheless, compared with other algorithms, the algorithm in this paper can maintain high positioning accuracy even under large distance errors of observation stations.

In conclusion, through detailed data analysis, we have verified the advantages of using a ConvBiLSTM-neural-network-enhanced TDOA ranging model in error control. This improvement not only improves the accuracy and reliability of the positioning system, but also increases the robustness of the model to noise.

Compared with other comparative algorithms, the algorithm proposed in this paper has significant advantages in positioning accuracy. As the measurement error of time difference decreases, the improvement of the positioning accuracy continues to increase, thus verifying the effectiveness of our algorithm. However, as shown in Fig. 9, when the measurement error of time

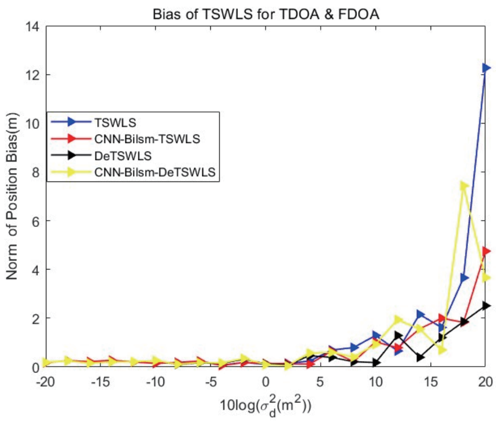

Fig. 8. (Color online) Plots of position error.

difference exceeds 10 dB, the positioning accuracy improvement rate of our algorithm weakens. This is mainly because, as the measurement error of time difference increases, it gradually becomes the dominant factor affecting the positioning accuracy. Although the introduction of the distance information of the observation stations still helps to improve the positioning accuracy at this time, its effect gradually weakens.

The simulation results show that the algorithm proposed in this study, which corrects the TDOA/FDOA values using ConvBiLSTM, significantly improves the target tracking performance compared with the original algorithm. In particular, the TDOA/FDOA values corrected by ConvBiLSTM are closer to the Cramer–Rao lower bound, which proves the effectiveness of the proposed algorithm in reducing the estimation error and improving the target tracking accuracy. In conclusion, in this study, we have verified the superior performance of the algorithm based on ConvBiLSTM for correcting TDOA/FDOA values in target tracking through simulation experiments. This algorithm can effectively reduce estimation error and improve target tracking accuracy. The simulation results are shown in Fig. 9 and Fig. 10.

5.2 High-speed tracking test

High-speed tracking tests are a key part of checking how well the ConvBiLSTM neural network works in dynamic situations, especially in locating and tracking fast-moving targets.

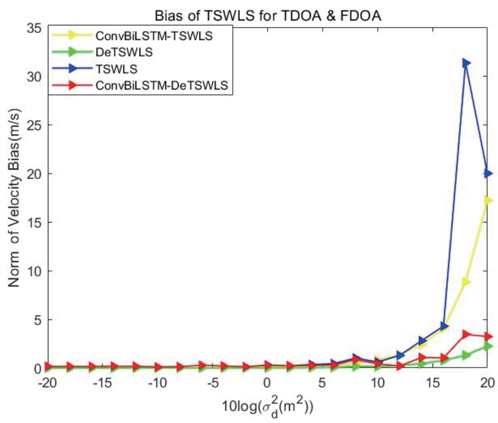

Fig. 9. (Color online) Plots of speed error.

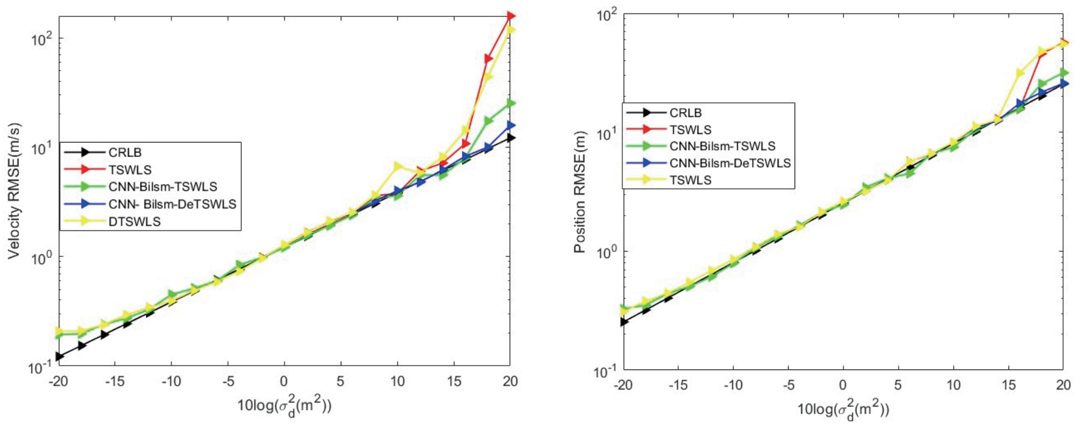

Fig. 10. (Color online) Position and speed of the algorithm for different observation station distances.

These tests are meant to simulate the complex movements of fast-moving targets in real-world situations. By comparing the model's output with the actual trajectory, we can see how well the network captures sudden changes and how stable it is over time. In the field of localization, research with high-speed moving targets can verify the algorithm's adaptability and responsiveness to rapidly changing environments. Moreover, it can help enhance the dynamic response capability of the localization system and its real-time data processing ability. Additionally, a radiation source is defined as a high-speed moving target when its relative speed with respect to Observation Station No. 1 exceeds 15 m/s. Five mobile observation stations were employed to observe the radiation source, and the parameter settings of the observation stations are presented in Table 2.

Compared with traditional algorithms such as TSWLS and DeTSWLS, the integrated algorithm proposed in this study demonstrates considerable advantages in velocity and position estimation accuracy under high-speed scenarios. When measurement noise is relatively low, the velocity *RMSE* and position bias of the proposed algorithm are significantly smaller than those of other methods, verifying the effectiveness of integrating CNN-based feature extraction and BiLSTM-based temporal modeling. However, as shown in experiments, when measurement noise exceeds approximately 15 dB, the algorithm's accuracy improvement capability diminishes because overwhelming measurement noise gradually becomes the dominant factor. Although the CNN module still extracts robust features from noisy data and BiLSTM models motion trends, their ability to compensate for considerable measurement distortion weakens as noise intensity surges, reducing the gain over traditional methods. The simulation results are shown in Fig. 11.

Table 2
Mobile observatory position and velocity parameter settings.

Station number	Station position *x*/*y*/*z* (m)			Station velocity *x*/*y*/*z* (m/s)		
1	300	100	150	20	−20	20
2	400	150	100	−20	10	20
3	300	500	200	10	−20	10
4	350	200	100	10	20	20
5	−100	−100	−100	−20	10	10

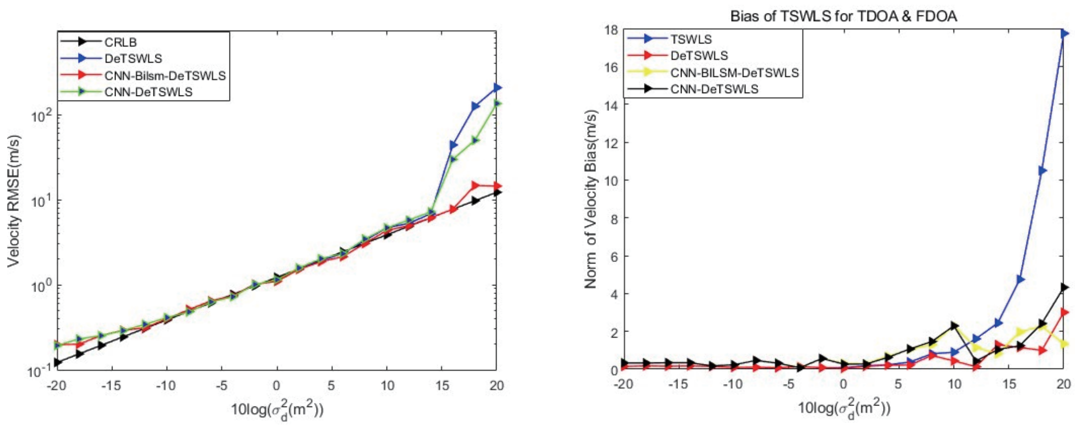

Fig. 11. (Color online) Error curves for state estimation of high-speed moving targets.

5.3 Long-distance testing

The known emitter target position is [200, 220, 300] and its velocity is [−20, 15, 40]. During the simulation, the ranging noise is set to 0.1. By continuously adjusting the size of the sensor disturbance error, the noise variance is controlled within the range of −20–20 decibels. In addition, targets with a spatial distance greater than or equal to 300 m between the emitter and Observation Station 1 are defined as long-range targets. The parameter settings for the remaining observation stations are shown in Table 1. The simulation results are shown in Fig. 12.

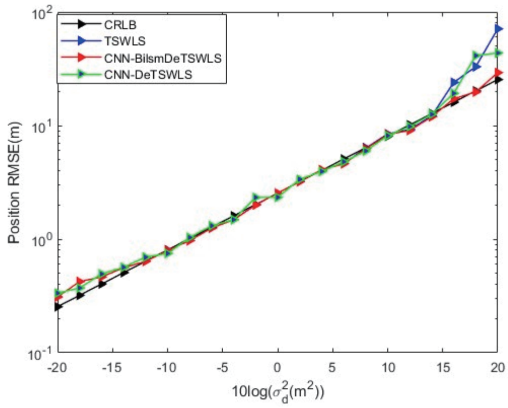

Fig. 12. (Color online) Error curves for state estimation of long-distance targets.

For long-distance radiation source localization scenarios, we simulate the complex effects of noise accumulation, signal time-varying distortion, and observation lag in long-distance propagation by adjusting the logarithmic scale of observation noise intensity. The experiment focuses on the *RMSE* of position estimation as the core indicator and compares the performance of traditional and fusion algorithms with the theoretical optimal accuracy limit. In weak noise environments (noise intensity logarithmic scale less than 5 decibels), the traditional algorithm TSWLS shows sensitivity to noise, and the error gradually deviates from the theoretical optimal accuracy limit. CNN DeTSWLS uses convolutional networks to extract multiscale noise features, suppress the distortion of long-distance signals, and achieve accuracy closer to the theoretical limit. CNN BiLstm DeTSWLS, on the other hand, performs better by utilizing bidirectional long short-term memory networks to mine the inertial laws of target motion and further correct errors in single frame observations.

Upon entering a strong interference scenario, the error of traditional TSWLS skyrockets sharply and its linear assumption completely fails under strong noise. Although CNN DeTSWLS can suppress some noise, the error still deviates significantly from the theoretical limit owing to the lack of modeling of "signal propagation lag". CNN BiLstm DeTSWLS uses bidirectional temporal modeling to predict the trajectory trend of the target in the forward direction and compensate for signal delay interference in the backward direction, resulting in the smoothest error growth.

5.4 Algorithm timeliness analysis

The ConvBiLSTM-DeTSWLS algorithm proposed in this study is designed with a time complexity centered on the principle of "adapting to the real-time requirements of actual moving target tracking". The specific complexity analysis is as follows.

(1) Position estimation in the algorithm: The computational load of this module is primarily concentrated in matrix operations, with a time complexity of $O(n^3)$, where n represents the dimension of the observation data. At this complexity level, the traditional TSWLS demonstrates high computational efficiency, enabling the rapid linearization and solution of nonlinear TDOA/FDOA equations, thereby establishing the foundation for the overall algorithm's temporal performance.

(2) Time complexity of the newly added ConvBiLSTM inference module: The ConvBiLSTM module is used for observation data correction. Although it sequentially performs convolution, pooling, and bidirectional long short-term memory operations, computational overhead is effectively controlled through optimized network structure parameters. Specific optimization measures include the following: fixing the convolution kernel size to reduce the number of spatial convolution operations, setting a reasonable number of hidden units to avoid redundant temporal computations, and configuring an appropriate dropout ratio to balance model performance and computational efficiency. Furthermore, network parameters remain fixed during inference, eliminating the need for retraining. Only forward propagation calculations on input observation data are required, keeping the additional time complexity within a controllable range without exponential growth.

(3) Overall algorithmic time complexity: The total time complexity of the ConvBiLSTM-DeTSWLS algorithm is the sum of the traditional TSWLS module complexity and the ConvBiLSTM inference module complexity, with no additional redundant computations. From an engineering perspective, this complexity design ensures that the algorithm's total runtime remains within the tolerance threshold for practical moving target tracking scenarios. For high-speed maneuvering targets, the optimized ConvBiLSTM inference efficiency and the improved iterative convergence speed of TSWLS still enable the overall duration to meet real-time requirements. This prevents tracking performance degradation owing to computational delays, satisfying the core demand for algorithmic time complexity in practical applications.

6. Conclusions

In this work, we proposed a distributed cooperative tracking algorithm that couples a ConvBiLSTM-based observation correction with a TSWLS estimator (DeTSWLS) for joint TDOA/FDOA localization. The network adapts measurements to time-varying noise by learning spatial patterns across stations and temporal trends over time, yielding corrected observations and uncertainty that drive dynamic weighting in the estimator. Simulations of routine, high-speed, and long-distance scenarios show consistent reductions in position and velocity *RMSE* compared with TSWLS/DeTSWLS baselines. Gains are strongest under moderate noise and taper when measurement errors become very large. End-to-end latency is modestly higher than that of traditional TSWLS but remains within real-time bounds. In future work, we will explore energy-aware implementations to extend node lifetime while maintaining tracking accuracy and system reliability.

Declarations

(1) Abbreviations
Not applicable
(2) Ethics approval and consent to participate
Not applicable
(3) Consent for publication
The authors give full permission for the publication of the article.
(4) Availability of data and material
Not applicable
(5) Competing interests
The authors have no conflicts of interest to declare. All coauthors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.
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