

Article

The Research of Air Combat Intention Identification Method Based on BiLSTM + Attention

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Abstract: In the process of air combat intention identification, expert experience and traditional algorithm are relied on to analyze enemy aircraft combat intention in a single moment, but the identification time and accuracy are not excellent. In this paper, from the dynamic attributes of an airspace fighter air combat target and the dynamic and time series changing characteristics of the battlefield environment, we introduce the bidirectional long short-term memory neural network (BiLSTM + Attention) intention identification method based on the attention mechanism for air combat intention identification. In this method, five kinds of state parameters, including target maneuver type, distance, flight velocity, altitude and heading angle, were taken as datasets. The BiLSTM + Attention was used to extract enemy aircraft intention features. By introducing attention mechanism, the weight coefficients of characteristic states corresponding to air combat victories were corrected. Finally, it was input into the SoftMax function to obtain the category of the enemy's intention. Experimental results showed that the proposed method can effectively identify enemy aircraft in the case of high complexity, multidimensional and large amount of data. Compared with bidirectional long short-term memory (BiLSTM), long short-term memory (LSTM), long short-term memory based on attention mechanisms (LSTM + Attention) and support vector machine (SVM) classification, the proposed method had higher accuracy and lower loss value.

Keywords: BiLSTM; attention mechanism; intention identification; air combat



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1. Introduction

Artificial intelligence (AI) is more agile than the human brain. The application of air combat intention identification method supported by AI enables pilots to extricate themselves from complex and massive information situations and quickly complete an OODA (Observation Orientation Decision Action) loop, one step ahead of the enemy. It also enables them to master the air combat situation and seize the air superiority. The research of the combat intention identification method in air combat is a practical practice of putting intelligent technology into fighter free air combat and is the key technical support for the air force aviation to win the battle. The traditional data-driven air combat intention identification methods mainly include module matching, expert experience, evidence theory, etc. For example, JinQ et al. [1] determined Bayesian network parameters based on expert experience. When an intention exceeds a specified value, it is the intention of identification. With the development of neural networks and deep learning technologies, these technologies have been widely used in combat intention identification. For example, Li Zhanwu et al. [2] proposed an improved long short-term memory neural network method for target intention identification in air combat based on the attention mechanism. The method is effective for air combat intention identification, but LSTM is a one-way propagation network that cannot be mined to exploit data information from future moments. Ou Wei's team [3] proposed an air combat intention identification based on the long short-term memory neural network addressing the intention identification as a time series change

feature. However, the neural network weights corresponding to different moments of the air warfare intention category are different, which requires a reasonable allocation of the weight coefficients corresponding to each air warfare intention feature state. Moreover, the data of the target feature set used in air warfare during the implementation of countermeasures show temporal and multidimensional changes, which cannot accurately identify the tactical operational intentions of enemy aircraft from the complex air warfare environment in real time by relying only on expert experience and single-moment feature information. The algorithm with both memory and forgetting functions can play its own advantage in mining the intrinsically related feature states of such data.

To address the above problems, this paper combines the attention mechanism and the structural characteristics of the LSTM neural network, introducing the BiLSTM + Attention-based air combat intention identification method to identify air combat intention. Through experiments, it is proved that the proposed identification method has higher identification accuracy and lower loss value than BiLSTM, LSTM, LSTM + Attention, SVM and another four methods, which can accurately and rapidly process multiple temporal and dynamic attributes hidden in air targets in long time sequence state clusters in the data set, and can provide pilots with accurate and rapid identification of enemy aircraft intentions in free air combat. These experiments can provide a reference for pilots to accurately and quickly identify enemy aircraft intentions in free air combat.

2. Mapping Relationship between Characteristic State Parameters and Combat Intention

Establishing an intention identification method for target is the premise of the intention category to provide a clear definition and description [4], namely, determining air combat intention space. Combined with the specific actual combat background, combat task and combat mode, the enemy target can have different air combat intentions. For example, in reference [5], in a spatial drone war as the research object, the enemy targets of tactical intention space for reconnaissance, surveillance, feint, attack, penetration, the front and retreat were established into 7 categories. In reference [6], for UAVs performing combat missions in certain airspace, the tactical intention space of enemy targets was defined as reconnaissance, attack, surveillance and cover (4 categories). In reference [7], the tactical intention space of the enemy target was defined as attack, reconnaissance, penetration and retreat for the target formation on the sea surface. This paper studies the problem of target intention identification of fighter aircraft in airspace, and establishes the tactical intention space of enemy aircraft into 5 categories (penetration, attack, feint, reconnaissance, retreat).

According to the expert knowledge in the field of air combat and the air combat experience of pilots, all kinds of combat intentions are mainly related to the state parameters such as the relative distance R of the target, the flight velocity V_T , the altitude H , the azimuth angle ϕ_T , the heading angle ϕ_s and the flight acceleration a_T . The target intention is finally implemented through maneuvers. Types of maneuvers can reflect the target's movement information and are closely related to combat intention. Tables 1–5 list the corresponding relationship between target distance, maneuvering type, altitude, velocity and heading angle of 5 characteristic state parameters and combat intention [8].

Table 1. The relationship between target distance and air combat intention.

Target Distance/km	Most Likely Combat Intention	Sub-Likely Combat Intention
<100	penetration	attack
100–300	attack	feint
300–500	reconnaissance	attack
>500	retreat	reconnaissance

Table 2. The relationship between maneuvering type and air combat intention.

Target Maneuvering Type	Most Likely Combat Intention	Sub-Likely Combat Intention
Fig-8	reconnaissance	feint
Fig-0	reconnaissance	feint
climb	attack	retreat
swoop	attack	penetration
snake-type maneuver	reconnaissance	feint
rear tracking turns	attack	feint
horizontal scissor maneuver	attack	feint

Table 3. The relationship between target altitude and air combat intention.

Target Altitude/m	Most Likely Combat Intention	Sub-Likely Combat Intention
50–200	penetration	attack
200–1000	reconnaissance	attack
1000–8000	attack	reconnaissance
8000–10,000	attack	feint
>10,000	reconnaissance	penetration

Table 4. The relationship between target velocity and air combat intention.

Target Velocity/km/h	Most Likely Combat Intention	Sub-Likely Combat Intention
600–850	reconnaissance	penetration
850–950	penetration	reconnaissance
950–1250	feint	reconnaissance
1250–1470	attack	retreat

Table 5. The relationship between target heading angle and air combat intention.

Target Heading Angle/°	Most Likely Combat Intention	Sub-Likely Combat Intention
0–20	penetration	attack
20–60	attack	penetration
60–90	reconnaissance	attack
90–180	retreat	reconnaissance

Since the operational intention of enemy aircraft is a dynamic time series process, relying solely on the state of enemy aircraft at a given moment to predict their next air combat operational intention is limiting and does not allow for a comprehensive situational awareness assessment [9]. In this paper, BiLSTM + Attention is used, respectively, to identify the intention of the characteristic datasets composed of target altitude, maneuver type, distance, velocity and heading angle. The essence of this mechanism is to extract the air tactical characteristic information of enemy targets from the continuous, real-time and dynamically changing air combat situation data. Based on the characteristics of neural network, the relationship between air combat intention category and enemy target characteristic state parameters is established. Finally, the test set data were input into the method generated after neural network learning and training optimization to verify the feasibility of the air combat intention identification method based on the attention mechanism of bidirectional long short-term memory network. The tag coding of five types of enemy targets' combat intention types is shown in Figure 1.

reconnaissance	coding →	0
penetration		1
feint		2
attack	← analysis	3
retreat		4

Figure 1. Air combat intention coding and pattern analysis.

3. Air Combat Intention Identification Method Based on BiLSTM + Attention

The linear sequence structure of a recurrent neural network (RNN) makes it very suitable for dealing with time series problems. However, due to its long back-propagation path, it is easy to cause gradient disappearance and gradient explosion [10]. The BiLSTM + Attention proposed in this paper is a new neural network developed based on RNN, which inherits the advantages of RNN. The BiLSTM + Attention can simulate the forgetting mechanism and memory mechanism of the human brain through the gated thought in a long short-term memory neural network. Therefore, it can overcome the problem of gradient disappearance or gradient explosion in the process of long-term series training. The bidirectional long short-term memory network can not only use historical information, but can also use information from future moments to make judgments on the current input datasets. The attention mechanism can highlight the feature states that account for a larger proportion of identification results by calculating the corresponding feature state weights of the feature vectors input from the neural network at different times, so as to make the intention identification method show better performance. This paper proposed the intention identification method based on BiLSTM + Attention and will be divided into three parts: the input layer, the hidden layer and the output layer. As shown in Figure 2.

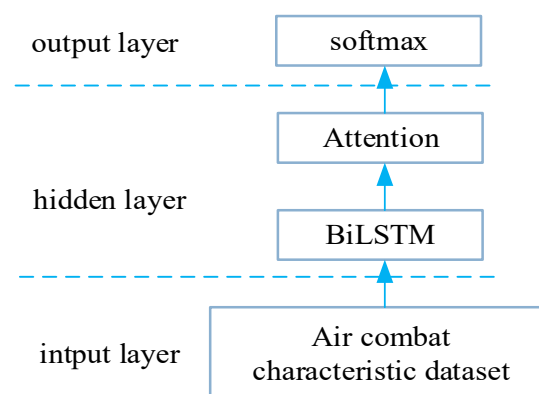


Figure 2. The BiLSTM + Attention intention identification method diagram.

3.1. Input Layer

If all information is considered to affect the identification result, instead of considering which part of the historical and future information, it will undoubtedly cause information redundancy and lead to a decrease in identification accuracy [11]. From the perspective of time sequence of air combat feature data sets, the input layer of this paper identifies target air combat intention by extracting time series of historical and future information. As with traditional machine learning, the input layer requires pre-processing the collected air warfare feature datasets into a form of feature vectors that the BiLSTM in the implicit layer can directly accept and can process.

3.2. Hidden Layers

The hidden layer contains the attention mechanism layer, BiLSTM layer and dense layer. The design concept of the intention identification method of BiLSTM is to make the feature data obtained at the moment have the information between the past and the future. As can be seen from Figure 3, the BiLSTM network of a single layer is formed by vector splicing of two LSTM networks, one for forward processing sequence and the other for reverse processing sequence. The two networks connect the same input and output layers. At moment t , $\vec{h}_t$ is the output of the forward LSTM and $\overleftarrow{h}_t$ is the output of the backward LSTM. The final output of the Bi-LSTM network at that moment is obtained by splicing the outputs of the forward and backward LSTMs, and the outputs of the two LSTMs are spliced together after the processing is completed. After the processing is completed, the output of the two LSTMs will be spliced together. In this way, not only historical information can be captured, but also future moment information can be extracted [12].

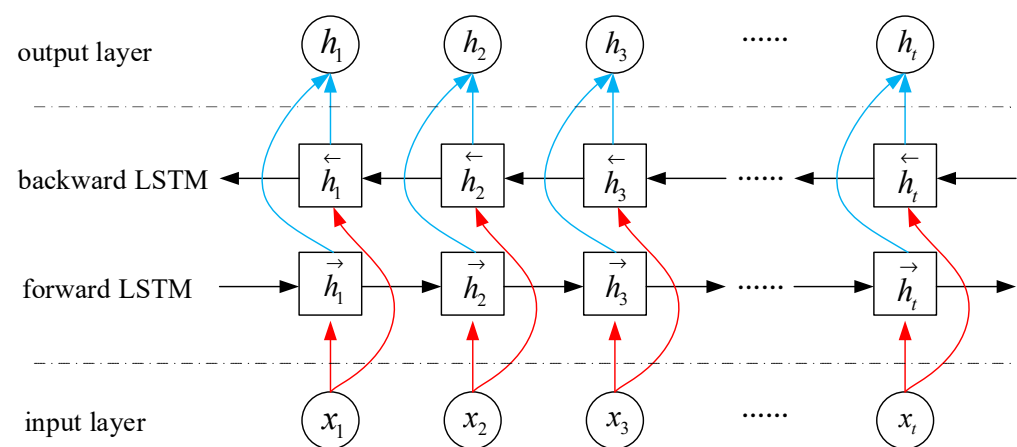


Figure 3. The BiLSTM deep neural network.

As shown in Figure 4, the LSTM is mainly composed of a circulating nucleus, a threshold (including input gate, forgetting gate and output gate), a cellular state, a memory and a candidate state. Where i_t is the input gate, f_t is the forget gate, o_t is the output gate, x_t is the input feature at the current moment, C_t is the cellular state of long-term memory, h_t is the memory of short-term memory and $\tilde{C}_t$ is a candidate state with the function of summarizing new knowledge [13,14]. Compared with the traditional RNN, LSTM adds a kind of memory unit for preserving historical information in its structure, which controls and updates the historical information iteratively by introducing the mechanism of gating, thereby being able to learn the intrinsic dependencies over long-range sequences and complement the shortcomings of gradient explosion and gradient disappearance in recurrent neural networks, so LSTM is regarded as a breakthrough progress of RNN [15]. The temporal unfolding structure of RNN is shown in Figure 5. Due to its design characteristics, LSTM has a good interaction effect on classification tasks such as strong positive meaning, weak positive meaning, neutral meaning, weak negative meaning and strong negative meaning when classifying at a finer granularity. It is very suitable for modeling of time series data, such as text data and feature set. At the same time, using LSTM networks can better capture longer distance dependencies. Although it is possible to learn what information is remembered and what information is forgotten through the LSTM training process, one of the larger problems with modeling data using LSTM is the inability to encode information from back to front [16]. To complete the shortcomings of a single LSTM and strengthen the absorption of sequential information, this paper introduced the air combat intention identification method based on the attention mechanism, which can effectively extract historical information and future information.

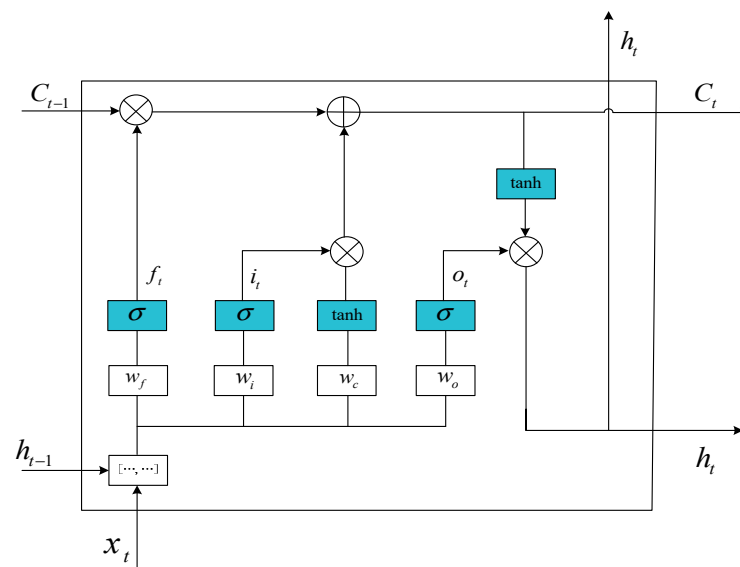


Figure 4. The diagram of LSTM block.

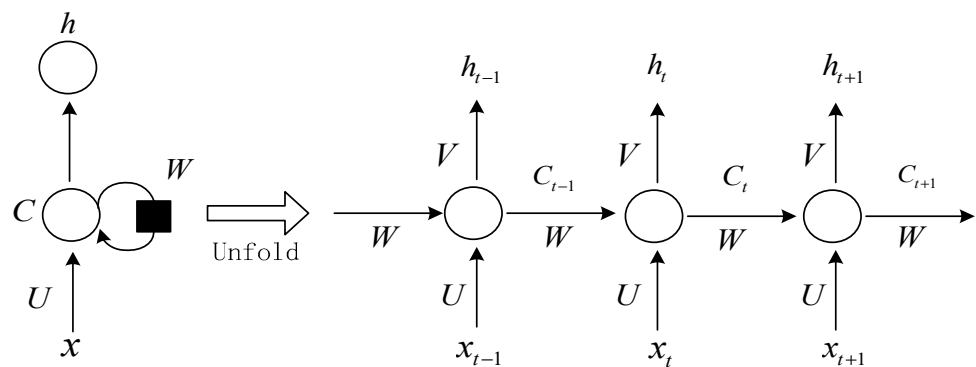


Figure 5. The diagram of RNN.

3.3. Attention Mechanism

The attention mechanism can imitate the human way of understanding everything in the world, which can resolve the problem of complex calculation of the magnitude and proportion of what components contribute to the data in the automatic input attention mechanism, and is often used in deep learning techniques in combination with models such as machine learning algorithms [17]. The attention mechanism is a special digital signal processing mechanism discovered by computer research scholars during their research on the visual level and computer vision and is invoked by teams in the field of artificial intelligence to simulate the human brain in deep reinforcement learning algorithms to solve some problems with proud results. Nowadays, the attention mechanism is widely used in the field of natural language processing in deep learning for machine translation, text classification, etc., highlighting the powerful ability of the attention mechanism in processing long and short-term time series feature tasks. The attention mechanism extracts a small amount of relevant information from the sample data, focuses on important information that is intrinsically relevant to the intention category and ignores most irrelevant information [18]. Moreover, its attention process to the sample feature states is reflected in the weight coefficient of the mechanism, and the larger the weight coefficient, the higher the attention to the sample feature states suitable for intention identification. The air warfare intention identification method focuses on the main features of the sample information through the attention mechanism during the training and learning process, the essence of which is to assign the appropriate weight coefficients through the learning of the neural network [19,20]. In this paper, the adaptive features and learning characteristics of neural

networks are used to learn the importance of each feature in the sample data of the training enemy aircraft intention category, and thus assign an appropriate weight coefficient to each feature [21]. The basic mechanism of the Attention mechanism is shown in Figure 6. In this paper, we use the adaptive and learning characteristics of neural networks to learn the importance of the features of each sample data set for training the enemy aircraft intention category, and then assign a corresponding weight coefficient to each feature. For example, when the enemy aircraft is a reconnaissance intention, where the target's heading angle (60–90°), target speed (600–850 km/h), distance (300–500 km) and maneuver type (8-letter, 0-letter, snake maneuver) and other feature states are assigned more weights by the attention mechanism to deepen the memory, and thus a larger weight coefficient is assigned.

$$e_t = \tanh(w_t s_t + b_t), \quad (1)$$

$$\alpha_t = \exp(e_t) / \sum_{i=1}^t e_i, \quad (2)$$

$$Y = \sum_{t=1}^n \alpha_t s_t, \quad (3)$$

where e_t is the energy value determined by the state vector s_t of the t -th eigenvector. The w_t is the weight coefficient matrix for the t -th feature vector. The b_t is the offset corresponding to the t -th eigenvector, α_t is the weight coefficient, o_t is the t -th eigenvector output by the hidden layer. As can be seen from Figure 5, the initial state vector s_t can be obtained by entering o_t into the attention mechanism. Y is the final output state vector [22].

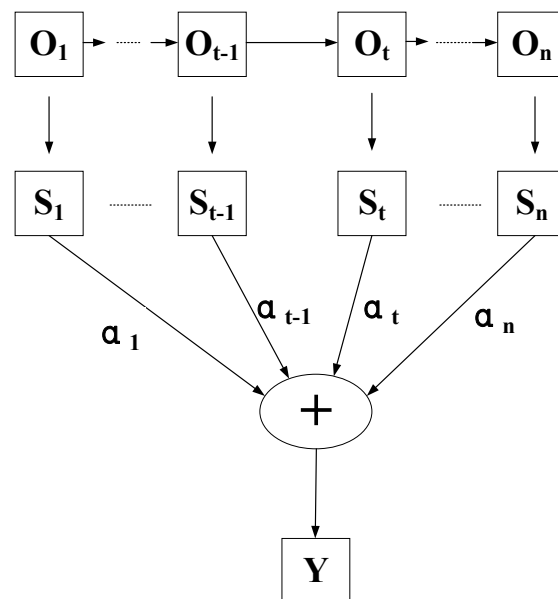


Figure 6. The Attention mechanism.

3.4. Output Layer

The output of the hidden layer enters the output layer as input data. Since the ReLU function has no saturation area, no gradient disappearance problem and simple operation and fast convergence, this paper uses the ReLU activation function to correct the eigenvalues. The SoftMax function can map the output of multiple neurons to the probability in the interval $[0, 1]$, which is used to solve the multi-classification problem [23]. In this paper, the categorical cross entropy loss function was applied in conjunction with the SoftMax function to assist SoftMax in extracting the maximum value among the values of the neurons and assigning a probability value to the results of each output intention

category as shown in Equation (4), where z_i is the output value of the i -th node and C is the number of output nodes, that is, the number of categories classified:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{c=1}^C e^{z_c}}, \quad (4)$$

4. Air Combat Target Intention Identification Process

Air combat intention identification is a process that takes place in a complex, highly adversarial environment, where enemy pilots also try to deceive our decision-makers as much as possible, forcing pilots to make incorrect judgments. In this paper, the air combat intention is identified by using multiple continuous time characteristics of the target, and the battlefield environment information such as the distance, maneuver type, course angle, altitude and velocity of the enemy is obtained through the radar. The bidirectional long short-term neural network based on the attention mechanism is used to combine with the corresponding air combat-related knowledge for self-learning and self-training to predict the combat intention of the enemy target.

$S = (i_1, i_2, \dots, i_n)$ is defined as the air combat intention space and I_t is defined as the time sequence feature composed by the feature set of T consecutive moments from t_1 to t_T . The mapping function of the air combat intention space S to the time series sequence is determined [24,25]:

$$S = f(I_t) = f(I^{(t1)}, I^{(t2)}, \dots, I^{(tT)}), \quad (5)$$

Due to the high uncertainty of the actual air combat environment, it is difficult to deduce the one-to-one mapping relationship from the sequence feature set to the intention type of air combat through the prescribed mathematical formula. This paper introduces the BiLSTM + Attention intention identification method for self-learning and self-training of feature state data to establish the mapping relationship between feature state and intention. Finally, the data of the test set is input for air combat intention identification and verification. In order to accurately describe the tactical intention identification method of an air target, the following assumptions are made:

(1) The tactical intention of air combat target does not change in the extracted time series;

(2) The battlefield environmental conditions such as the air combat climate, atmosphere and terrain of both sides are roughly the same.

The overall framework of the air combat intention identification method based on BiLSTM + Attention is shown in Figure 7 below. The method contains three modules, which are air combat feature data acquisition and processing module, BiLSTM + Attention intention identification method modeling and training optimization module and validation test module.

Module 1: The air combat feature data acquisition and processing module. Before the air combat intention identification, the status information of the target at N consecutive moments ($T_n \sim T_{n+N}$) should be collected in real time to obtain the complete training datasets. In order to eliminate the impact of data dimension and improve the scientific calculation, it is also necessary to normalize the data processed. For the i -th data $F_i = [f_{i1}, f_{i2}, f_{i3}, f_{i4}, f_{i5}]$. Mapping all the data in type i to the interval $[0, 1]$ and the result is f_i . The formula is:

$$f_i = \frac{f_i - \min F_i}{\max F_i - \min F_i}, \quad (6)$$

Module 2: The BiLSTM + Attention intention identification method modeling and training optimization module. The data sets processed by module 1 will be input into the bidirectional long short-term memory network based on the attention mechanism. The memory ability and forgetting mechanism of the bidirectional long short-term memory network will be used to capture the dependence of the feature data set on the front and back bidirectional time series in the identification of air combat intention, which finally output to the attention mechanism layer. By assigning different weights to the characteristic states

of different time series, the mapping relationship between the characteristic states of data and the type of air combat intention is obtained. Finally, there is continuous training and optimization of the BiLSTM + Attention neural network mapping in air combat intention identification.

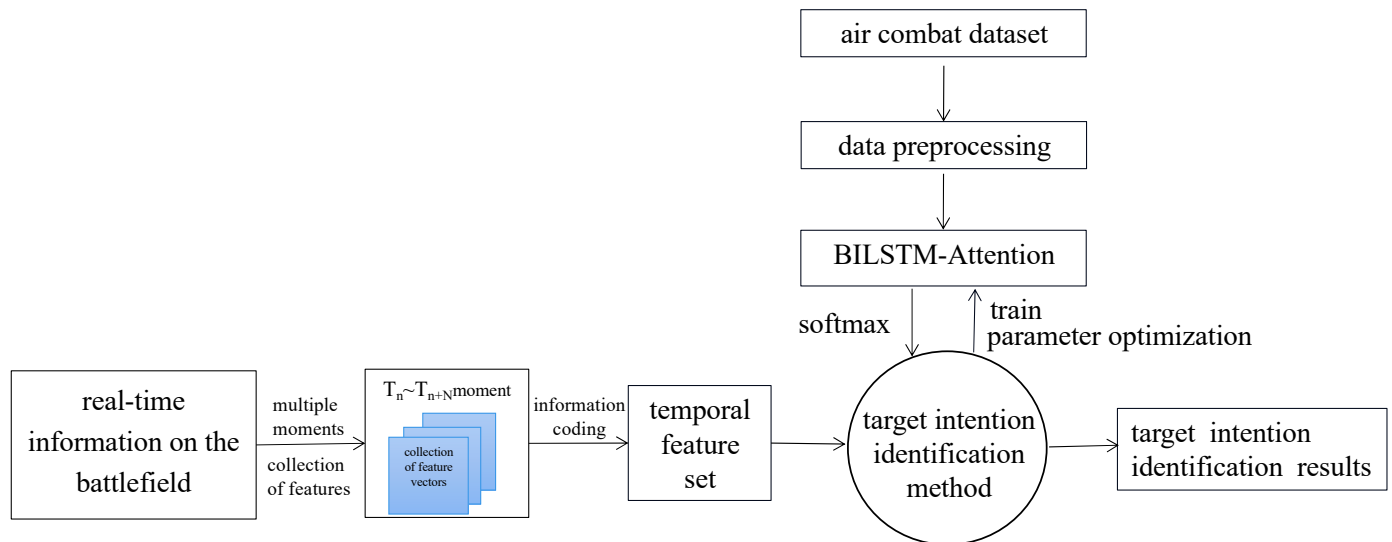


Figure 7. The intention identification process of BiLSTM + Attention.

In the process of establishing a mapping relationship, it is necessary to frame the time series with a time sliding window and use an optimizer function to improve learning efficiency for continuous training and optimization of the air combat intention identification method based on the BiLSTM + Attention algorithm. Among them, the sliding window is as to the principle of convolution or moving average, which can frame the time series according to the specified unit length, in order to calculate the statistical indicators in the box. It is equivalent to a slide block with a specified length sliding on the scale plane and the data in the slide block can be fed back with each sliding unit. Air combat intention identification data are common and important data objects. In view of the multi-dimensional and sequential characteristics of time series, direct training of original data to achieve regression prediction and other operations will ignore the sequential nature of time series, which will not only have low performance in computing efficiency, but also affect the accuracy and reliability of the algorithm and cannot achieve satisfactory results [26]. Sliding window has the advantages of strong operability, convenience and continuity. Through sliding window, every data input will be trained [27].

The Adam optimization algorithm is a learning rate adaptive optimization algorithm. The Adam algorithm can be understood as a stochastic gradient descent (SGD) adaptive optimizer supplemented with momentum method. It can replace the classical stochastic gradient descent method to update the network weight more effectively [28]. It is suitable for many kinds of problems, including models with sparse or noise gradient. The ease of fine-tuning makes it easy to achieve good results quickly. In fact, the default parameter settings often do the trick. The Adam optimizer combines the benefits of AdaGrad and RMSProp. It also uses the same learning rate for each parameter and adapts continuously as learning proceeds [29]. In addition, the Adam algorithm makes good use of historical information about gradients. Based on these characteristics, the Adam algorithm is often the best choice when selecting optimization algorithms.

Module 3: The validation test module. In order to verify the generalization ability and feasibility of the proposed air combat intention identification method, the data divided into test sets are input to the optimally generated air combat intent identification method based on the BiLSTM + Attention algorithm for intention identification, as well as to analyze

the accuracy rate and loss value change pattern to judge the generalization ability of the proposed intention identification method.

5. Experiment and Results

The experiments are conducted in the background of free air combat of a fighter aircraft in an airspace. In the simulation experiments of the intention identification method, the hardware configuration used for this calculation is a central processor CPU, AMD Ryzen 7 5800 H with Radeon Graphics 3.20 GHz, the RAM is 16 G; the graphics processor is NVIDIA GeForce GTX 1650 4 G. The calculation is performed using Tensor flow 2.5.1+ Python 3.9.12 + Win10 virtual environment. The experiment uses the accuracy and loss value of intention identification as the evaluation index of intention identification effect. A total of 5000 pieces of intention identification data are used in the experiments, which are exported in CSV files, among which about 80%, that is, 3972 pieces, are randomly selected as training samples; the remaining about 20%, that is, 1028 pieces, are used as test samples. The specific division of training and testing samples is shown in Table 6. In purchase to avoid the errors caused by different ranges of variables in the data, all sample data were normalized using Equation (6). The experiments were performed by a five-fold cross-validation with 50 iterations in each round and 100 iterations of the training set data after cross-validation.

Table 6. Classification of intention identification sample data.

Intention Type	Total Samples	Training Samples	Test Samples
penetration	1032	798	234
attack	996	797	199
feint	1056	844	212
reconnaissance	886	709	177
retreat	1030	824	206

5.1. Parameter Optimization

The basic parameters of the experiment directly affect the performance of intention identification. Therefore, before the experiment, we should carry out optimization research of its basic parameters to ensure the best accuracy of air combat intention identification.

5.1.1. The Effect of Sliding Windows on Identification

Different sliding window lengths will not only change the size of the data set, but also the size of the data contained in the segmented data, therefore, different sliding window sizes will affect the intention identification results. In this paper, six sliding window lengths of 8, 12, 16, 20, 30 and 40 were selected as the basis for the study of the effect of sliding window length on air combat intention identification results. Table 7 shows the accuracy and loss values of intention identification under different sliding window lengths. According to the results in Table 7, the accuracy rate increases and the loss value decreases as the sliding window length increases, but the accuracy rate decreases after the length 12. Therefore, the sliding window 12 is selected as the best sliding window length before starting the calculation.

Table 7. The effect of sliding window lengths on air combat intention identification.

Sliding Window Lengths	Accuracy	Loss
8	93.88%	0.188
12	99.12%	0.136
16	94.73%	0.185
20	93.12%	0.198
30	90.33%	0.223
40	88.12%	0.236

5.1.2. The Effect of Batch Size on Identification

Increasing the batch size can improve the computer memory utilization and the parallelization efficiency of large matrix multiplication, but too high of a batch size can also increase the time complexity. Thus, different batch sizes will affect the intention identification results. Therefore, this paper conducts a study on the effect of different batch sizes on intention identification and the resulting data are derived as shown in Table 8. According to the results in Table 8, it can be seen that the batch size 128 is selected as the batch size before starting the calculation.

Table 8. The effect of batch size on air combat intention identification.

Batch Size	Accuracy	Loss
32	86.66%	0.246
64	89.14%	0.138
128	99.23%	0.119
256	97.14%	0.166

5.1.3. The Effect of the Number of Hidden Nodes of Neural Networks on Identification

The experimental results vary with a different number of hidden layer nodes. Before this experiment, 30, 50, 70, 90 and 100 hidden layer nodes were set and the accuracy values tested in the simulation experiment were 93.12%, 95.53%, 98.53%, 94.66% and 93.88%, respectively. It can be seen that the number of hidden layer nodes is not the more the better, but there exists a suitable number of nodes and too many will cause an over-fitting phenomenon. Based on the results in Table 9, it can be seen that 70 was selected as the optimal number of network nodes before starting the calculation.

Table 9. The effect of the number of hidden layer nodes on air combat intention identification.

Hidden Nodes	Accuracy	Loss
30	93.12%	0.256
50	95.53%	0.167
70	98.53%	0.126
90	94.66%	0.192
100	93.88%	0.144

5.1.4. The Effect of Dropout on Identification

In machine learning, if the number of samples is too small and the training parameters are too large, the model is prone to over-fitting. To solve the problem of model over-fitting, Hinton proposed the dropout algorithm in his paper “Image Net Classification with Deep Convolutional Neural Networks”. In order to verify whether the introduction of dropout has any effect on the computational accuracy, this paper carries out the effect of having or not having dropout parameters and different dropout sizes on the computational results. The calculation results are shown in Table 10. From the table, it can be seen that the accuracy is weakened after the first improvement as the dropout value keeps increasing. Therefore, the accuracy of the identification method increases first and then decreases with the increase of dropout and the best effect of intention identification is achieved when dropout = 0.1.

Table 10. The effect of dropout on identification.

Dropout	Accuracy	Loss
0.0	94.12%	0.132
0.05	96.53%	0.182
0.1	97.93%	0.131
0.2	96.16%	0.262
0.3	92.34%	0.168

5.1.5. The Effect of Learning Rate on Identification

In machine learning algorithms, a learning rate set too small leads to a slower convergence of the neural network, and too large leads to a network that fails to converge and hovers around the optimal value. From Table 11, it can be seen that as the learning rate value keeps increasing, the accuracy increases first and then decreases, and the loss value decreases first and then increases, so that the best result of intention identification is achieved when the learning rate = 0.1.

Table 11. Effect of learning rate on air combat intention identification.

Learning Rate	Accuracy	Loss
0.001	95.12%	0.152
0.01	96.31%	0.182
0.1	99.61%	0.131
0.2	95.33%	0.239

Comprehensive analysis of the above experiments, using training samples for identification methods for multiple training, comparing the identification accuracy and loss values of the test samples under different parameters and finally, the experimental parameters selected and set for this experiment are shown in Table 12.

Table 12. Experimental parameter setting.

Parameter Name	Numerical Value
sliding window lengths	12
batch size	128
learning rate	0.1
dropout rate	0.1
activation function	ReLU
hidden nodes	70

5.2. Result Analysis of Identification Method Based on BiLSTM + Attention

After the training of BiLSTM + Attention intention identification method, 1028 samples of data were tested. The experimental results are shown in Figure 8 and Table 13. The confusion matrix is an $n \times n$ matrix that summarizes the prediction results of classification methods in machine learning. The real labels of the confusion matrix are marked in the first row, while the prediction labels are marked in the first column. The number of correctly classified and identified samples of each classification is on the diagonal line and the data in the remaining positions can represent the number of samples wrongly classified into other categories. In this paper, when applying the confusion matrix, the number of samples is divided by the total number of samples in the category to obtain the corresponding identification rate. In the research of intention identification, the confusion matrix can be used to directly understand the identification rate of each kind of intention by the identification method, as well as the cases where specific intention is misjudged as other kinds of intention. As can be seen from the confusion moments of intention identification in the simulation experiment results in Table 13, the accuracy rates of the

five types of intention identification methods proposed in this paper reach 98.9%, 99.3%, 98.6%, 99.35% and 99.55%, respectively. That is, the accuracy rates of air combat intention identification verified by each training are stable at around 99%. It can also be seen from the confusion moment of intention identification that the accuracy rate of the five types of intention identification is relatively high, especially the accuracy rate of retreat intention identification which reached 99.55%. The identification rate of attack intention is low, which is easy to be misjudged by the identification method as other categories of intention.

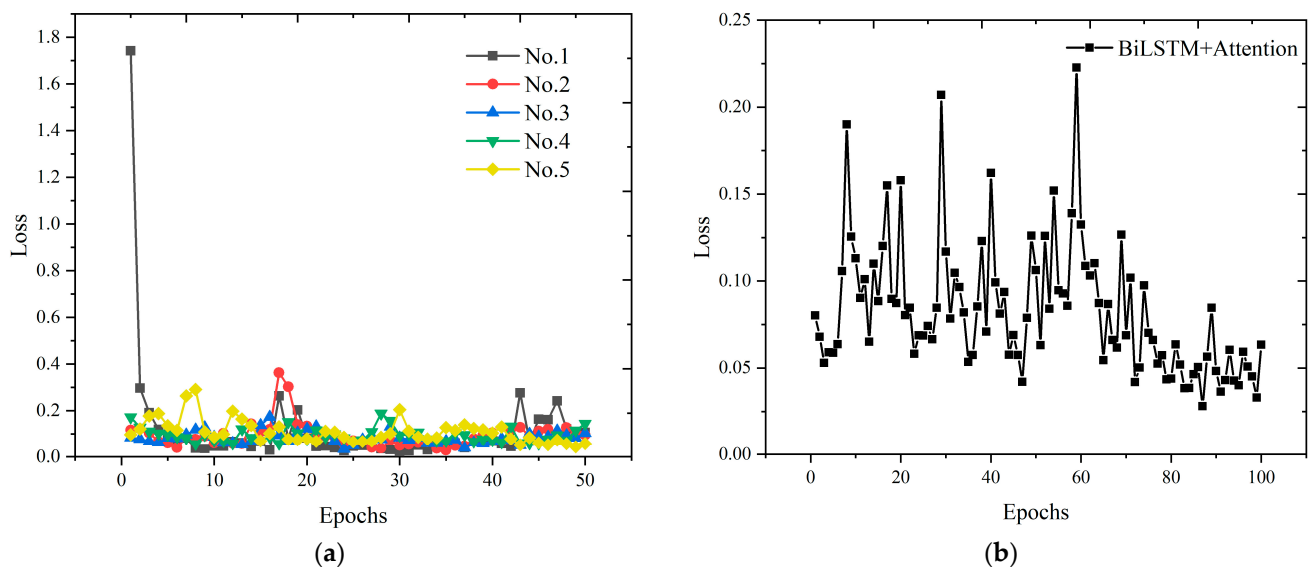


Figure 8. This is a figure of the loss value of BiLSTM + Attention simulation experiment: (a) The loss value of 50 iterations; (b) The loss value of 100 iterations training data.

Table 13. Confusion matrix of intention identification methods.

Intention Type	Feint	Reconnaissance	Attack	Penetration	Retreat
feint	98.90%	0.99%	0.11%		
reconnaissance	0.22%	99.30%		0.48%	
attack	0.13%	0.15%	98.60%	0.95%	0.17%
penetration		0.17%	0.48%	99.35%	
retreat		0.45%			99.55%

As can be seen from the change curve of intention identification loss value in Figure 8, with the increase of the number of training iterations, the loss value of the five categories of air combat intention fluctuates greatly in the early stage. After the 60th iteration, the curve begins to converge and the loss value tends to a certain lower range. It shows that after the optimization of the Adam optimizer function and multiple training sessions, the identification method gradually learns the identification rules and how to avoid the paths that lead to training errors. The average identification accuracy rate of this method is 99.14% and the average probability of training failures and inefficiencies is also maintained below 8%. That is, the proposed intention identification method has learned how to identify enemy target intentions from real-time continuous feature states accurately and effectively.

5.3. Comparative Experiment of Five Intention Identification Methods

In order to further verify the feasibility and effectiveness of the proposed identification method, in the case of the same experimental parameters and experimental environment, this paper conducts comparative experiments and analyses of five identification methods: BiLSTM + Attention, LSTM, BiLSTM, LSTM + Attention and SVM. Table 14 shows the accuracy of the five intention identification methods and Figures 9–12 show the change of

loss curves during the training of the four intention identification methods: BiLSTM, LSTM, LSTM + Attention and SVM. The horizontal coordinate in the figure indicates the number of training iteration epochs, while the vertical coordinate is the loss value of the dataset validation. The lower and more stable loss value indicates the less variability between the target value and the predicted value.

Table 14. The Comparison accuracy of the five identification methods.

Identification Methods	Five-Fold Cross-Verification Accuracy					Average Accuracy	Average Time/ms
BiLSTM + Attention	98.60%	99.10%	99.50%	99.80%	98.70%	99.14%	51.82
BiLSTM	95.55%	98.87%	97.85%	98.62%	98.37%	97.87%	51.30
LSTM	94.61%	95.75%	96.86%	92.52%	94.12%	94.77%	49.53
LSTM + Attention	96.36%	97.12%	95.26%	98.26%	96.29%	96.66%	50.33
SVM	89.23%	94.19%	95.11%	92.12%	94.95%	93.12%	59.16

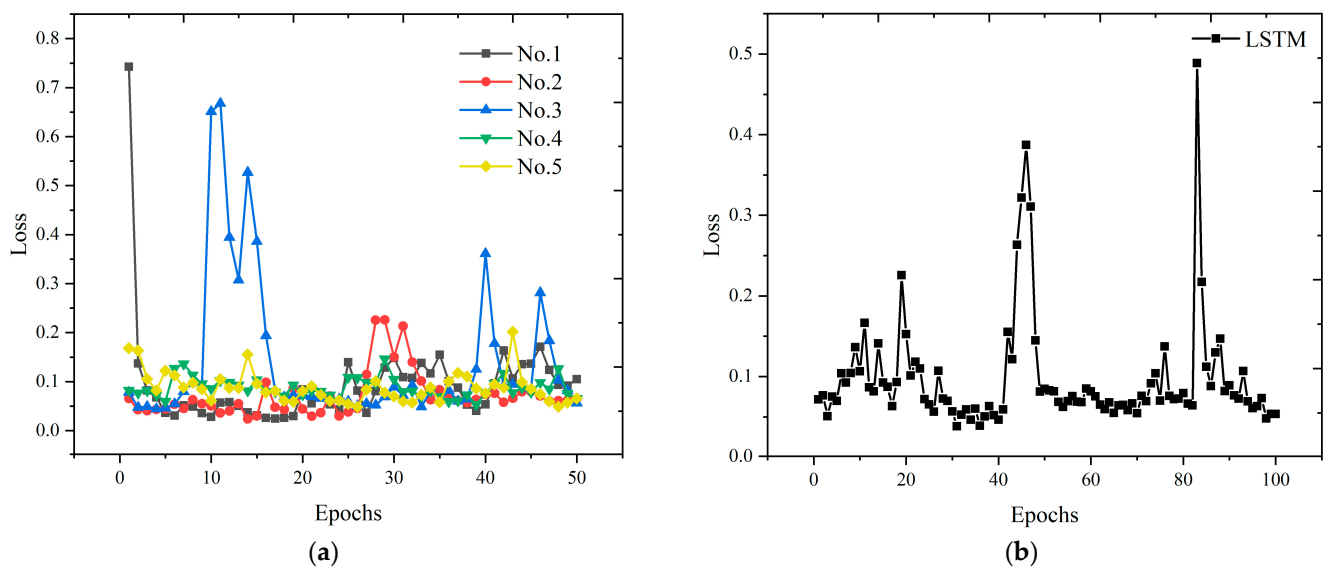


Figure 9. This is a figure of the loss value of LSTM simulation experiment: (a) The loss value of 50 iterations; (b) The loss value of 100 iterations training data.

From the comparison of the results in Figures 8–12, it can be seen that the overall change rule of training loss value is similar when using the five network optimization algorithms. The loss value of the proposed intention identification method tends to stabilize faster after a certain number of training iterations and the loss value is lower. Moreover, the error range is small and it has higher stability. As can be seen from Table 14, the intention identification accuracy of air combat intention identification based on BiLSTM + Attention proposed in this paper is 99.14%, 4.37%, 1.27%, 2.48%, 6.02% higher than that of BiLSTM, LSTM, LSTM + Attention and SVM, respectively. It shows that the intention identification method based on BiLSTM + Attention algorithm has higher accuracy. In terms of the average identification time for a single intention, BiLSTM + Attention, BiLSTM, LSTM, LSTM + Attention and SVM are 51.82 ms, 51.30 ms, 49.53 ms, 50.33 ms and 59.16 ms, respectively. The running times of the identification methods based on the long short-term memory neural network correlation algorithms do not significantly differ. It is concluded from the analysis that the running time complexity of SVM increases in the case of large and multidimensional data samples. By comparing the accuracy rate and the loss value of the experiment, it can be seen that compared with the single LSTM neural network, the BiLSTM memory network has more advantages in processing classification problems, which is more conducive to extracting the information before and after the sequence and capturing the features of the data set. In addition, the LSTM + Attention intention identification method

based on LSTM introduces the attention mechanism, which can increase the attention to important features by increasing the weight of feature states that have a greater impact on free air combat. That is, increasing their corresponding weight coefficients, highlighting the information that is more critical to victory in free air combat, so the method has a higher accuracy than the LSTM intention identification method. A visual representation of the accuracy of the five identification methods is shown in Figure 13.

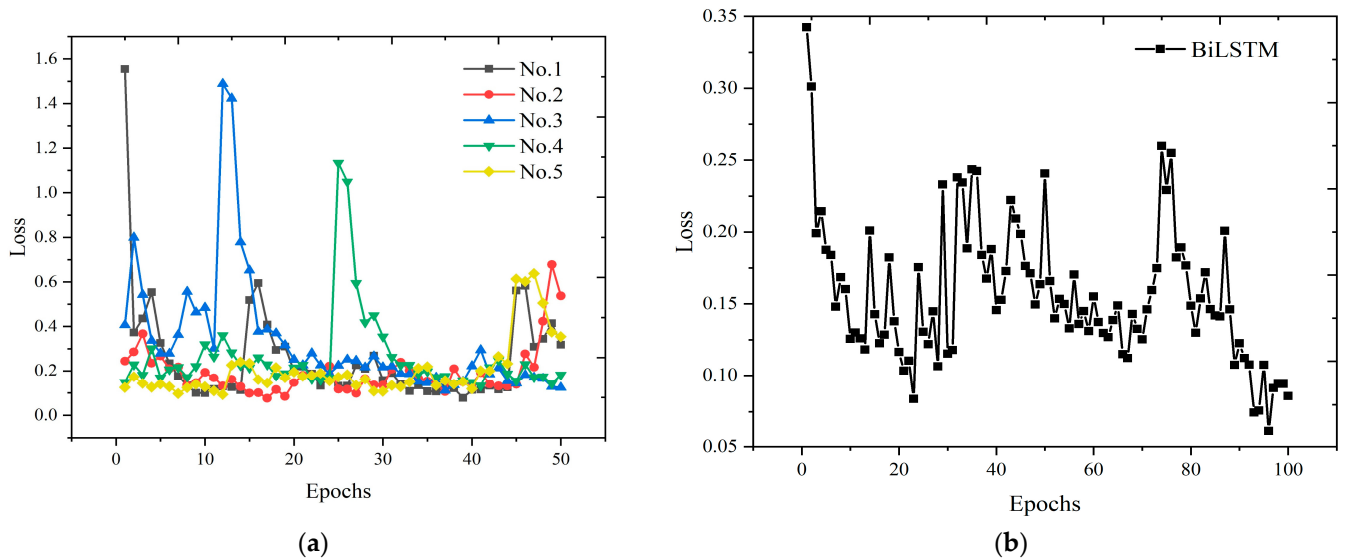


Figure 10. This is a figure of the loss value of BiLSTM simulation experiment: (a) The loss value of 50 iterations; (b) The loss value of 100 iterations training data.

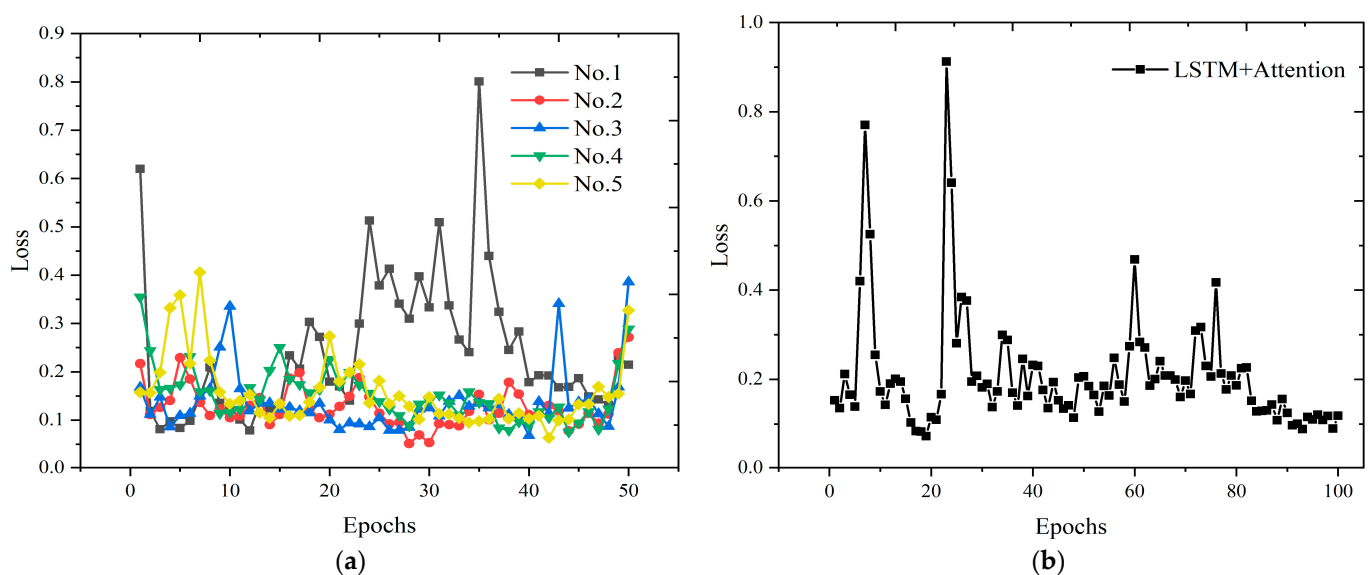


Figure 11. This is a figure of the loss value of LSTM + Attention simulation experiment: (a) The loss value of 50 iterations; (b) The loss value of 100 iterations training data.

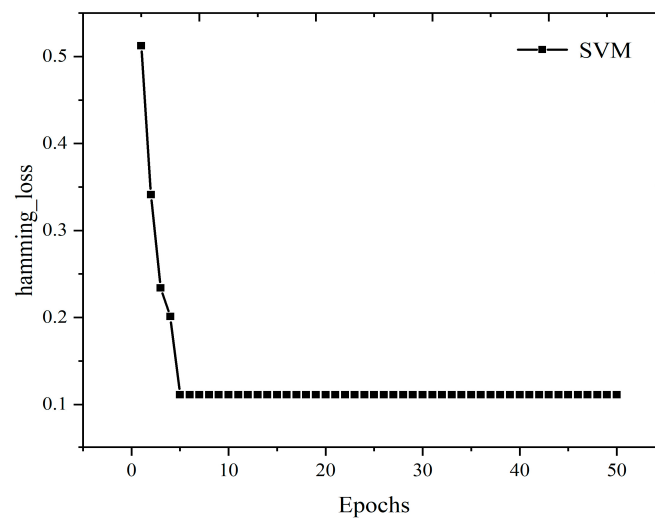


Figure 12. The loss value of SVM simulation experiment.

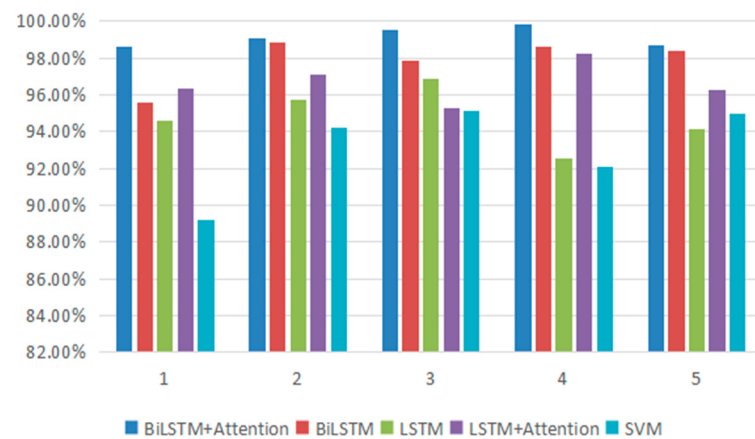


Figure 13. The accuracy of the five identification methods.

5.4. Ablation Experiments by Intention Identification Methods

From the comparison experiments between BiLSTM + Attention and LSTM, BiLSTM, LSTM + Attention and SVM intention identification methods, it can be seen that the proposed method has the characteristics of high accuracy and low loss value. However, this does not belong to the comparison of the same type of experimental methods, which lacks certain experimental persuasiveness. Therefore, the same type of ablation experiments of BiLSTM + Attention and LSTM, BiLSTM and LSTM + Attention was conducted in the same data sets to further eliminate the influence of characteristic variables on experimental results. Three machine learning indexes: precision rate (Pre), recall rate (Rec) and F1 fraction value, were introduced to evaluate four combat intention identification methods in air combat.

The precision rate refers to some intention identification results from the right sample of intention identification method for determining intention for the sample proportion. The recall rate refers to the proportion of the number of samples correctly identified by a certain intention to the actual number of samples. In the following equations, F1 score is the average of precision rate and recall rate where m represents some kind of intention category ($m = 1, 2, 3, 4, 5$). TP is the number of correct results for certain intentions, FN is the number of errors identified by a certain intention and FP is the amount of intention

misjudged by other intention identification results. The ablation experiment is shown in Table 15.

$$P_{re} = \frac{TP_m}{TP_1 + TP_2 + TP_3 + TP_4 + TP_5}, \quad (7)$$

$$Rec = \frac{TP_m}{TP_m + FN_m}, \quad (8)$$

$$F1 = \frac{2 * P_{re} * Rec}{P_{re} + Rec}, \quad (9)$$

Table 15. The ablation experimental results of four identification methods.

Comparison of the Model Components			Accuracy %	Loss Value
Bidirectional	LSTM	Attention		
✓	✓	✓	99.14	0.059
✓	✓		98.37	0.103
	✓	✓	96.29	0.112
	✓		94.77	0.169

As can be seen from Table 15, the accuracy rate and loss value of the proposed method are significantly better than LSTM, BiLSTM, LSTM + Attention and other intention identification methods. After analysis, it is concluded that the bidirectional propagation mechanism can effectively improve the training effect. The neural network can learn faster with the same learning rate, batch size, epochs and retention rate. ①, ②, ③ and ④ in Table 16 represent BiLSTM + Attention, BiLSTM and LSTM + Attention, respectively, and LSTM intention identification methods. The accuracy of the four methods for detection and retreat intention identification is high, but the identification rate for attack intention is low. The analysis shows that the characteristic states corresponding to attack intention are more complex and the distance (100–300 km), velocity (1250–1470 km/h), height (1000–8000 m), 8000–10,000 m), maneuver type (climb, dive, rear tracking turn, horizontal scissors motorized), heading angle (20–60°) and other characteristic states are associated with it. There are a variety of mapping relationships which are easy to be confused. Among the four identification methods, there is little difference between the three evaluation indexes, but the air combat intention identification method based on BiLSTM + Attention is superior to the other three methods in various evaluation indexes. This indicates that the identification method proposed in this paper is more conducive to effective identification of continuous, real-time and dynamic air combat feature datasets.

Table 16. Comparison of the performance of four identification methods.

Evaluation Metrics		Precision Rate				Recall Rate				F1 Score			
		①	②	③	④	①	②	③	④	①	②	③	④
air combat intention	feint	99.1	98.1	96.6	94.3	99.3	98.5	96.4	94.5	99.2	98.3	96.5	94.4
	reconnaissance	99.5	97.3	97.2	94.8	99.1	96.5	96.4	93.6	99.3	96.9	96.8	94.2
	attack	98.6	97.1	95.8	88.9	98.6	98.3	95.8	89.3	98.6	97.7	95.8	89.1
	penetration	97.9	96.2	96.3	94.6	97.3	98.4	96.5	94.8	97.6	97.3	96.4	94.7
	retreat	99.8	97.9	95.8	93.4	99.2	98.5	96.8	92.8	99.5	98.2	96.3	93.1

6. Conclusions

This paper introduced an air warfare intention identification method based on BiLSTM + Attention by using the adaptive and self-learning characteristics of a bidirectional long short-term memory neural network and the attention mechanism, which solves the problems of low identification accuracy and poor effect in the traditional air warfare intention identification process to reach the real-world level. Through simulation comparison experi-

ments with BiLSTM, LSTM, LSTM + Attention and SVM, as well as ablation experimental research, the proposed method's air warfare intention identification capability is verified. The proposed identification method can assist pilots to make accurate and rapid decisions and put into action countermeasures by using deep reinforcement learning technology in the case of inexperienced experts, which can provide reference value for auxiliary combat equipment and is of great significance to the development of daily aviation equipment simulation training and military intelligence.

(1) The proposed identification method has good applicability for past and future time series prediction, which can extract the correlation features between target feature state parameters and combat intention well. The average correct recognition rate for the five categories of intention was 99.14%, with an average identification time of 51.82 ms for a single intention, which proves that the proposed method can accurately and rapidly identify all kinds of combat intention and has good identification performance.

(2) The results of comparison experiments and ablation experiments of identification methods show that the proposed identification method outperforms BiLSTM, LSTM, LSTM + Attention and SVM in two evaluation indexes: identification accuracy and loss value. It is proved that the back-and-forth bidirectional propagation mechanism, memory function, forgetting mechanism and attention mechanism in the proposed identification method can more effectively deal with the dependency relationship in the datasets, deal with the datasets with temporal and dynamic characteristics and explore the causal logic relationship embedded in the target intention.

Combined with the research work of this paper and the future development direction, we should also continue to explore in two aspects: First, to expand the scope of application of the intention identification method, that is, the problem of air combat intention identification under the multi-aircraft cooperative system. The second is the problem of air warfare intention identification in which the data feature states are similar and easily lead to confusion of identification results.

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