Recognition of Combat Intention with Insufficient Expert Knowledge

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Keywords: Combat intention, Deep neural network, Recognition.

Abstract. Aiming at the problem that the relationship between targets’ state feature and combat intention cannot be quantified under the condition of insufficient expert knowledge, a combat intention recognition model based on deep neural network is designed. By introducing the ReLU activation function and the Adam optimization algorithm, the convergence speed of the model is improved, and the local optimization is effectively prevented. The experimental results show that the proposed method can effectively recognize the target’s combat intention and obtain better recognition results.

Introduction

The recognition of enemy target combat intentions is a hot topic in the field of situation assessment, and is an important basis for our commanders to make decisions. Under the conditions of informationization, the complexity and transience of modern battlefields have increased dramatically, it is difficult for commanders to process a large amount of battlefield information in a short period of time and recognize the enemy’s combat intentions. This requires the combat command system to assist commanders in making decisions to shorten the decision-making time and improve the quality of decision-making. The aerial combat target is a typical combat platform in modern warfare and an important force for capturing air superiority. The timely and accurate recognition of aerial target combat intention provides strong support for air defense combat command. The existing researchs on combat intention recognition mainly based on template matching [1-3], expert system [4-6], Bayesian network [7-9] and neural network [10-13] to recognize the intention of targets. Although methods described in [1-9] solve the problem of target combat intention recognition to a certain extent, they require a large number of domain experts knowledge to quantify the weight or prior probability of the intention recognition feature. However, with the increasing complexity of the battlefield environment, the emergence of new combat platforms and combat styles, it is difficult for domain experts to grasp the comprehensive information of the target in a short time. Aiming at the above problems, reference [10-13] use the neural network adaptive and self-learning capabilities to automatically extract recognition rules from the training feature data and store the recognition rules in the weights of the network for the prediction of intentions. These neural network-based methods can solve the problem of target intent recognition better when the domain experts have insufficient prior knowledge. However, due to the shallow network layer, it is difficult to express the problem of high complexity. These methods adopt Back Propagation(BP) algorithm to train the network, which has a slow convergence rate and is easy to fall into local optimum.

Aiming at the difficulty to quantify the mapping relationship between attribute features and combat intentions under the condition of insufficient knowledge of domain experts, a method of combat intention recogniton based on deep neural network is proposed. Deep neural network is a multi-hidden layer neural network. Due to the deep network layer, the back-layer network can form higher-level features based on the preliminary features learned in the front-layer network [14], so it can get better recognition effect. In this paper, the Rectified Linear Unit(ReLU) function [15] is used as the activation function to solve the gradient disappearance problem. At the same time, the Adaptive
Moment Estimation (Adam) [16] optimization algorithm is used to accelerates the model convergence and jumps out the local optimum. The deep neural network method can solve the problem of target intention recognition better under the condition of insufficient knowledge of domain experts.

**Combat Intention Recognition Based on Deep Neural Network**

For the neural network with multiple hidden layers, the back-layer network can form higher-level features based on the preliminary features learned by the front-layer network [14], so that the data features can be better characterized, and at the same time, compared to the single hidden layer, A multi-node neural network can characterize functions of the same complexity with fewer parameters. With the increase of network complexity, the basic BP neural network is more likely to fall into local extremum, resulting in the network not being well trained. The BP algorithm uses chain derivation to update the weight. As the number of network layers increases, the gradient disappears, resulting in a nearly paused training process and difficulty in convergence. Deep learning is a branch of machine learning. Its goal is to establish a neural network that can simulate human brain for analysis and learning. It has been widely used in image recognition, speech recognition, and behavior recognition and other fields.

**ReLU Activation Function**

If the gradient neural network node weight is updated by the gradient descent method, when the partial derivatives of each layer are less than 1, then as the recursion proceeds, the gradient becomes smaller and smaller, causing the gradient to disappear almost. The commonly used activation functions of BP neural network are Sigmoid function and tanh function. The Sigmoid function maps variables to [0,1], and the tanh function maps variables to [-1,1], when the function approaches the saturation region, its derivative approaches 0. When the BP algorithm is used to update the weight, each layer is passed backwards, and the gradient is attenuated to 0.25. Deep neural network based on these two activation functions will be more likely to disappear as the depth of the network deepens, and it is delayed to converge.

The expression for the activation function ReLU is \( \sigma(z) = \max(0, z) \). It’s easy to calculate the derivative for him. When \( z \geq 0 \), the derivative is 1, and when \( z < 0 \), the derivative is 0. Therefore, gradient decay does not occur with recursion, and partial gradient disappearance can be solved.

**Model Training Process Based on Adam Algorithm**

The learning rate of the traditional gradient descent method remains unchanged, and as the complexity of the loss function increases, it is easier to fall into the "saddle point", that is, the gradient value is zero in all directions. The Adam algorithm combines the advantages of the Momentum optimization algorithm and the RMSprop (Root Mean Square Prop) optimization algorithm. When the gradient is continuously updated in the same direction, the weight will be increased. When the gradient update direction changes, the weight will be reduced. Just like the inertia in the process of falling stones. Using this "inertia" can avoid falling in the local best in network training and accelerate network convergence. At the same time, the Adam algorithm can make the parameters adaptively update the learning rate. The parameter learning rate with high update frequency is small, and the parameter learning rate with low update frequency is large, which can improve the robustness of the gradient optimization algorithm.

**Target Combat Intention Recognition Process**

The target combat intention is recognized based on the deep neural network model, and the steps are as follows:

**Step 1** The target feature data are extracted from various types of sensors, and the tag is marked according to actual combat results and domain expert judgments. The database is constructed from the acquired target feature data and the intention tag. A part of the database is extracted as the test
database, and the other part is used as the training database. A part of the data is randomly extracted from the training database as a verification database;

Step 2  Adjust the network structure and determine the number of network layers and the number of nodes.

Step 3  Input all the data in the training database into the constructed deep neural network and adjust the network weights. Compare the output intent recognition result with the label and calculate the recognition accuracy. If the recognition accuracy reaches the established standard of the model, go to step 4, otherwise go to step 2;

Step 4  Input the data in the verification database into the trained deep neural network and calculate the recognition accuracy. If the recognition accuracy reaches the established standard of the model, go to step 5, otherwise go to step 2;

Step 5  Input the target feature data in the test database into the trained deep neural network and determine the model recognition effect according to the recognition accuracy;

Step 6  Input the target feature data of combat intention to be recognized into the model to recognize its combat intention.

Simulation Experiment and Analysis

The combat intentions are divided into 8 categories: penetration, attack, electronic interference, transportation, refueling, civil aviation flight, early warning detection and reconnaissance. Extracting feature state measurements corresponding to eight combat intentions State measurement values corresponding to eight combat intention were extracted, and a total of 8000 sets of measurement data were extracted. Randomly extract 90% of the data to form the training database, and the remaining 10% constitute the test database. The experimental iteration step size is 10000, neural network learning rate $\eta = 0.01$, hyperparameter $\beta_1 = 0.9$, $\beta_2 = 0.999$, and smoothing term $\varepsilon = 10^{-8}$.

Experiment to Determine the Model Structure

Different neural networks have different recognition effects for deep neural networks. Therefore, it is necessary to determine the number of hidden layers and the number of nodes in the deep neural network model. Although the model effect is judged by the test data, the test data cannot be used to adjust the model structure in the experiment. Using test data to adjust the network structure can lead to model overfitting and loss of ability to discriminate against unknown data. Randomly extracting 10% of the data in the training database to establish a verification database. Using the verification database to judge the effect of the model and adjust the model structure.
It can be seen from Figure 1 that the curve trend of the verification data set and the test data set are basically the same, so the verification data set can be used to judge the quality of the model and adjust the model structure. It can be seen from Figure 1(c) that when the number of network layers is 4 and the number of nodes is 10, 20, 20, 10, the accuracy of model recognition is high, so it is determined that the structure of the deep neural network model is 10, 20, 20, 10.

**Experiment to verify the Reliability of Model**

In order to verify the reliability of the proposed model, 90% of the data is extracted from the database in 8 sessions to form the training sample, and the remaining 10% of the data constitute a test sample. Inputing the training sample to the model to adjust the parameters of the node, and then using the test sample to judge the model recognition effect.

| Training accuracy | Test accuracy | Average test accuracy |
|-------------------|---------------|-----------------------|
| 0.9824            | 0.9816        |                       |
| 0.9743            | 0.9625        |                       |
| 0.9857            | 0.9908        |                       |
| 0.9683            | 0.9724        |                       |
| 0.9904            | 0.9873        |                       |
| 0.9875            | 0.9835        |                       |
| 0.9917            | 0.9910        |                       |
| 0.9836            | 0.9846        | 0.9817                |

It can be seen from Table 1 that the deep neural network model can effectively identify the aerial target's combat intention under different training sample conditions, and the average recognition rate is 98.17%, which verifies the reliability of the proposed model.
Experiment to Verify the Accuracy of the Model

In order to verify the accuracy of the proposed model, the experimental results were compared based on the single-layer BP neural network model, the deep BP neural network model, the Adam+Sigmoid deep neural network model and the Adam+ReLU deep neural network model. The following are the results of the comparison of the four models.

Comparing the accuracy curves of the four models to the aerial target's combat intention recognition, it can be seen that the Adam+ReLU deep neural network model converges faster than the other three models, and it converges around 1300 iterations, and the recognition accuracy is the highest.

Summary

An aerial target combat intention recognition model based on deep neural network is designed and optimized by ReLU function and Adam algorithm. The experimental results show that the deep neural network model has good reliability and accuracy for recognizing aerial target combat intention. The results of the contrast experiment show that the improved deep neural network algorithm has faster convergence speed and better recognition effect.

References

[1] D F Noble, Schema-based Knowledge Elicitation for Planning and Situation Assessment Aids, IEEE Transactions on Systems Man & Cybernetics, 1989, 19(3): 473-482.
[2] W Jiang, D Han, X Fan, et al, Research on Threat Assessment Based on Dempster–Shafer Evidence Theory, Green Communications and networks, 2012: 975-984.
[3] M Li, X X Feng, W Zhang, Template-based Inference Model and Algorithm for Situation Assessment in Information Fusion, Fire Control & Command Control, 2000, 35(6): 64-66.
[4] M Ben-Bassat, E Freedy, Knowledge Requirements and Management in Expert Decision Support Systems for (Military) Situation Assessment, Systems Man & Cybernetics IEEE Transactions on, 1982, 12(4): 479-490.
[5] Z Q Wu, D F Li, A Model for Aerial Target Attacking Intention Judgment Based on Reasoning and Multi-Attribute Decision Making, Electronics Optics & Control, 2010, 17(5): 10-13.
[6] R Carling, Naval Situation Assessment Using A Real-Time Knowledge-Based System, Naval Engineers Journal, 2010, 111(5): 108-113.
[7] Q Jin, X Gou, W Jin, et al, Intention Recognition of Aerial Targets based on Bayesian Optimization Algorithm, IEEE International Conference on Intelligent Transportation Engineering. IEEE, 2017: 356-359.

[8] A Dahlbom, A Comparison of Two Approaches for Situation Detection in an Air-to-Air Combat Scenario, Modeling Decisions for Artificial Intelligence. Springer Berlin Heidelberg, 2013: 70-81.

[9] Z G Chen, X F Wu, A Novel Multi-Timescales Layered Intention Recognition Method, Applied Mechanics & Materials, 2014, 644-650: 4607-4611.

[10] S Y Jia, J Y Xu, Y Wang, Classification of Air Target Intention based on Adaptive Neural Network Fuzzy System(ANFIS), Electronic Measurement Technology, 2016, 39(12): 62-66.

[11] B Liu, Quantitative Method of Targets Attack Intention Based on ANFIS, Command Control & Simulation, 2012, 34(5): 14-17.

[12] H Chen, Q L Ren, Y Hua, et al, Fuzzy Neural Network based Tactical Intention Recognition for Sea Targets, Systems Engineering and Electronics, 2016, 38(8): 1847-1853.

[13] A A Ahmed, F M Mohammed, Sairf: A Similarity Approach for Attack Intention Recognition Using Fuzzy Min-max Neural Network, Journal of Computational Science, 2018, 25: 467-473.

[14] G E Hinton, R R Salakhutdinov, Reducing the Dimensionality of Data with Neural Networks, Science, 2006, 313(5786): 504-507.

[15] X Glorot, A Bordes, Y Bengio, Deep Sparse Rectifier Neural Networks, International Conference on Artificial Intelligence and Statistics, 2011: 315-323.

[16] D P Kingma, J Ba, Adam: A Method for Stochastic Optimization, Computer Science, 2014.