An Intelligent Evaluation Model for Decision Scheme Based on Deep Learning

Wei Ou¹,*, Zhaohui Yi¹, Lan Cheng¹, Ying Liao²

¹The Border and Coastal Defense College, Urumqi, China
²China National Digital Switching System Engineering & Technological R&D Center, Zhengzhou, China

*Corresponding author e-mail: ouweiwlmq@163.com

Abstract Studying and constructing the intelligent decision-making model for simulation entity can effectively improve the credibility and immersion of wargaming, in which intelligent evaluation of decision scheme is the key module. To lower the reasoning complexity and shorten the decision time, an intelligent evaluation model based on Stacked Auto-Encoder (SAE) is proposed, which simulates the reasoning mode of human decision-making, and learns commander's knowledge and experience through unsupervised and supervised training. Then, to improve the robustness and generalization ability of the deep learning model, a de-noising training method and sparsity constraints are introduced. Finally, simulation experiment is carried out to verify the scientficity and effectiveness of the proposed model.

1. Introduction

Wargame has been widely used in command and decision training, tactical analysis and other fields. Studying and constructing the intelligent decision-making model of simulation entity, will effectively improve the credibility and immersion of wargaming. Decision-making behavior of simulation entity is a special decision-making problem, which follows the general laws of combat decision, also has certain particularity in goals, conditions and process. Decision scheme evaluation is used to measure the possible achievement of alternative schemes, which is the core content of combat decision-making and the basis for selecting schemes. Where, the possible achievement of combat scheme is not only related to the decision conditions, but also affected by various random events and the overall evolution trend of battlefield situation. Thus, it is difficult to introduce a simple and clear mathematical formula to describe the complex relationship. Compared with combat decision-making in actual battlefield, thousands of decision-making behavior needs to be processed simultaneously in wargame system. Thus, the computing time, space and other resources allow entities to consume are more limited. Therefore, to reduce the consumption of resources in the decision-making process, it is necessary to design an intelligent evaluation model, which can simulate the reasoning mode of commander and possessing efficient hidden rules fitting ability and feature extraction ability.

2. Basic consideration of the intelligent model

Due to the fuzziness and comprehensiveness of combat objectives and various random factors in combat process, it is difficult to construct a clear mathematical model to describe the complex relationship between them with decision scheme. The method of effect evaluation based on wargaming simulates the interaction process of various complex factors, so it is much more scientific
and credible. But in wargame system, dealing with the decision-making behavior of thousands of entities at the same time are need. If the evaluation method based on wargaming is still adopted, it is hard to meet the demand of time, computing and storage resources. In view of this, this paper introduces an deep neural network (DNN) as the evaluation module, as shown in Figure 1.

![Figure 1](image)

**Figure 1** evaluation process based on deep learning

The core idea of the intelligence evaluation model based on DNN is abstracting and learning the knowledge and experience from the past simulation data about "the action effect obtained by adopting the corresponding decision scheme under different conditions in the past operation". Thus, the excellent memory, association, generalization and parallel computing ability of DNN is used to extract hidden features and deep rules in the historical data, then unsupervised feature learning and supervised network training are combined to learning the knowledge and experience of commanders.

3. Design of intelligent evaluation model

3.1. Basic framework of intelligent evaluation model

Stacked Auto-Encoder (SAE) \(^{[3,4]}\) is a typical DNN model, which possesses excellent ability of abstracting feature and fitting complex laws. Therefore, and intelligent evaluation model based on SAE is proposed, as shown in Figure 2.

![Figure 2](image)

**Figure 2.** Basic framework of intelligent evaluation model

SAE takes Auto Encoder Neural Network (AENN) as basic unit, each unit contains an encoder and a decoder. The basic idea of SAE is to encode the input signal to output signal, then reconstruct the output signal by decoding it. Then, the reconstructed signal is compared with the original signal to calculate the reconstruct errors, and then let AENN learn how to minimize the reconstructed errors. The AENN is stacked up layer-by-layer, and then a Logical Regression (LR) is added to the top. Hence, the intelligent evaluation based on SAE mainly includes two basic steps: first, constructing
3.2. Basic process of intelligent evaluation model

The process of intelligent evaluation model based on SAE is shown in Figure 3.

![Figure 3. The process of intelligent evaluation algorithm](image)

The basic process of the proposed model is as follows:

1. Select and extract the relevant information from real-time battlefield data, which includes the battlefield environment information in corresponding space-time domain, the state information of relevant combat entities, etc., then formed it and get initial feature set.

2. The attributes and state feature information of related entities in successive times \( (T_n \sim T_{n+h}) \) are collected and then stored by stack, to form a set of feature vectors.

3. Normalize and encode the feature data, forming a standardized sequence feature set.

4. Generate a feasible decision scheme satisfying the constraints by combat scheme generator, or get a decision scheme given by commander.

5. Encode the time series feature set, decision scheme and decision target as input signals of the intelligent evaluation model.

6. Intelligent evaluation model based on DNN is used to predict the action effect of decision-making scheme, and then output the evaluation result through pattern analysis.

3.3. De-noising training and sparsity restriction

The battlefield data which operational decision-making depends on are often opaque, incomplete, or even deceptive. In order to mine the hidden features and laws in these data, it is necessary to improve the robustness of feature extraction. Previous studies have demonstrated that, adding noise to input signal according to a certain probability, and then training the model to learn how to reconstruct the original signal from the signal containing noise, will effectively improve the robustness and generalization ability of the SAE model. The model trained according to the above process is called Denoising Auto-encoder (DA)[5].

In addition, combat data is complex, high-dimensional and sparse. Intelligent evaluation model should have good ability to mine hidden patterns and complex laws from high-dimensional and sparse combat data. Studies have shown that when the human brain is stimulated by external stimuli, most of the neurons are inhibited, and only a small number of neurons are highly activated. Sparse Auto-encoder (SA) simulates the sparse response mechanism of human brain, uses a "super-complete" base vector to describe data samples [6]. Therefore, for any input signals, only a few neurons are allowed to respond and be activated, forcing all neurons in a state of inhibition for most time.

Combining the advantages of the above methods, a Stacked Sparse De-noising Auto-encoder (SSDA) model is proposed. Where, SAE is used to simulate the layer-by-layer feature extraction process of human brain, noise training is introduced to enhance the robustness and generalization, and sparsity restriction is used to enhance the ability of mining the complex structure, pattern and law. Thus, the trained SSDA can not only make use of the good feature learning ability of deep neural network, but also possess robustness performance and anti-jamming ability.
3.4. Knowledge acquisition method of intelligent model

Compared with other intelligent model based on machine learning, SSDA has certain advantages in knowledge representation, knowledge renovation and knowledge learning. The intelligent evaluation model based on SSDA learn the knowledge and experience by adopting a knowledge learning method named "end-to-end", which deduces the implicit mapping relationship from training sample set to pattern space. Knowledge acquisition of proposed model mainly includes four stages:

Firstly, a sample set for training SSDA models is constructed. According to the previous analysis, each training sample in the sample set mainly describes the basic factors that commanders need to consider when decision reasoning, such as "current battlefield situation and its evolution trend", "the state of the combat environment and its change trend", "the basic characteristics of behavior and state changes of related simulation entities", etc..

Then, add pattern label for each sample, establishing a mapping from the sample set to the pattern space. That is, on the basis of abstracting and summarizing the operational laws, principles and experience, explore the relationship of "what operational effect will be by adopting different decision schemes for specific objectives under the corresponding combat conditions".

Finally, military experts and researchers use their knowledge and experience to validate and modify the sample and label set, and then train SSDA model by "end-to-end" method using the large-scale data set generated, so as to integrate knowledge and experience into DNN model and transform them into intelligent model as network parameters.

4. Simulation experiment

Based on the data and rules of wargame system, the experiment environment is reconstructed and the data samples are extracted. Then, constructs a non-overlapping training sample set (including 20 000 samples), a validating sample set (including 2 000 samples) and a testing sample set (including 2 000 samples). Firstly, based on multi-layer perceptron (MLP)\(^7\), SAE model and SSDA mentioned above, the decision-making effect evaluation model is implemented by using the same input feature coding method and pattern space definition method. Then the data set is used to train the above models, and the basic parameters of each algorithm model are shown in Table 1.

| Model  | Parameters setting                                                                 |
|--------|-----------------------------------------------------------------------------------|
| MLP    | Supervised learning times \( \varepsilon_p = 3000 \); learning rate \( \zeta_1 = 0.04 \); batch size \( N_b = 400 \); hidden layer number \( HN' = 1 \), node number \( HLZ' = [4096] \). |
| SAE    | Unsupervised learning times \( \varepsilon_p = 200 \), Learning rate \( \zeta_2 = 0.02 \); supervised learning times \( \varepsilon_p = 3000 \), learning rate \( \zeta_1 = 0.04 \); batch size \( N_b = 400 \); hidden layer number \( HN = 3 \), node number \( HLZ = [2048, 1024, 512, 512] \). |
| SSDA   | Noise parameters \( PN = [0.05, 0.05, 0.05, 0.05] \), sparsity parameters \( \rho = 0.10 \), and other parameters keep consistent with the SAE. |

4.1. Convergence performance analysis

According to different models, the same training and validating sample sets are used, and the convergence of validating errors is statistically analyzed, as shown in Figure 4.
Figure 4 Convergence of intelligent models

As shown in Figure 3, the convergence speed of MLP model is slower, and the validation error is still about 49% when training iteration equals 3000. The performance of SAE model is obviously better than that of MLP model. The validation error of SSDA model is about 15.8% when the training iteration equals 3000. Comparing with SAE model, the convergence speed of SSDA is faster and the precision is much higher. Because of de-noise training and sparse constraints are introduced, SSDA model has a small vibration in the training process, but maintains a good convergence trend. When training iteration reaches 3000 times, the validation error decreases to about 4.9%.

4.2. Accuracy analysis of intelligent models

Then, the test sample sets are used to evaluate the Accuracy performance of trained model, and the accuracy of various evaluation models are calculated, as shown in Table 2.

| Intelligent models | accuracy |
|--------------------|----------|
| MLP                | 0.492    |
| SAE                | 0.845    |
| SSDA               | 0.946    |

Table 2 shows that, the prediction accuracy of the decision-making effect evaluation model based on different algorithms is quite different: the accuracy of MLP below 50%, SAE is obviously superior to MLP, and the accuracy is above 84.5%; the accuracy of SSDA model is the highest, reaching 94.6%. It can be seen that the SSDA model proposed in this paper has high accuracy and can reliably evaluate the action effect of the decision scheme.

5. Conclusion

Decision-making effect evaluation is the basis for simulation entities to choose decision scheme reasonably, so it is necessary to design an intelligent, efficient and reliable evaluation model. This paper constructs an intelligent evaluation model of decision scheme based on the Stack Auto-Encoder (SAE), which simulates the thinking mode and learns the knowledge and experience of human. Then, de-noising training and sparsity constraints are introduced to improve the robustness and generalization ability. The test results show that the proposed model has good convergence performance and prediction accuracy, and can evaluate the effect of decision scheme scientifically.

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