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Postprint: Application of an Improved DNN Algorithm in Radar Signal Sorting

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Date: 2018-05-02T00:00:00+00:00

Abstract

This study investigates the advantages of deep neural networks in automatically learning deep-level features from data, and proposes a signal sorting method based on deep belief networks to address problems in traditional radar signal sorting such as time-consuming manual feature extraction and feature redundancy. By stacking multiple layers of deep models to improve the original algorithm, the method overcomes the insufficient learning capacity of a single model, deeply learns the essential features of different signals, and fuses the posterior probabilities of each deep model for classification decision-making, thereby further improving the signal recognition rate. The improved method is employed for sorting and recognizing seven different types of radar signals, and compared with other signal sorting methods. Experimental results demonstrate that the proposed method achieves better classification performance and exhibits a strong capability to learn essential features from data, thereby validating the effectiveness and superiority of the algorithm.

Full Text

Preamble

Application of an Improved DNN Algorithm in Radar Signal Sorting

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Abstract: This paper investigates the advantage of deep neural networks in automatically learning deep-level data features and proposes a signal sorting method based on deep belief networks to address the time-consuming nature and feature redundancy problems associated with manual feature extraction in traditional radar signal sorting. By stacking multiple layers of deep models to improve upon the original algorithm, this approach overcomes the insufficient learning capability of single models, conducts in-depth learning of the essential features of different signals, and fuses the posterior probabilities from each deep model for classification decision-making, thereby further improving signal recognition rates. The improved method was applied to sort and recognize seven different types of radar signals and compared with other signal sorting methods. Experimental results demonstrate that this method achieves better classification performance and exhibits strong capability in learning the essential features of data, thus verifying the effectiveness and superiority of the algorithm.

Keywords: signal sorting; deep belief network; stacked multilayer model; posterior probability

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0 Introduction

Through the analysis and processing of large volumes of radar emitter signals accumulated over time, we can gain important insights for further research on radar types and threat characteristics. Deep neural networks (DNN), also known as deep learning, have emerged as a hot research topic in artificial intelligence algorithms in recent years. By simulating the human brain's analytical processes, DNNs combine and learn from low-level data to obtain more abstract high-level features that facilitate signal classification. Since its proposal in 2006, deep learning has found widespread applications in handwriting recognition, speech recognition, and image processing, with various models including deep belief networks, convolutional neural networks, and autoencoders.

Traditional pulse description word (PDW) features such as Time of Arrival (TOA), Radio Frequency (RF), Pulse Amplitude (PA), Pulse Width (PW), and Direction of Arrival (DOA) can no longer meet the demands of modern electronic warfare. In recent years, time-frequency features, wavelet packet features, and wavelet ridge frequency features have achieved good recognition results in signal identification. However, these features still present several considerations: the effectiveness and universality of feature extraction methods in signal recognition systems warrant further investigation, and the feature extraction process suffers from time consumption, insufficient manually-defined features, and feature redundancy. Obtaining strongly discriminative essential features of signals would significantly aid subsequent classifier design and recognition performance improvement.

With the rapid development of modern military technology, radar signals have become increasingly parameter-variable and complex, making signal sorting more challenging. Deep belief networks (DBN), as pioneers in constructing such deep neural network architectures, possess powerful data feature representation capabilities. They can establish a joint distribution between data and labels, learning deep-level relationships from raw samples as essential features for classification through hierarchical network training. DBN models can automatically and deeply learn the essential features of signals, making them suitable for signal sorting and recognition problems. However, single models suffer from insufficient learning capability and low precision. To address this, we propose an improved method by stacking multiple DBN models with different network structures: stacked deep belief networks (Stacking DBN). This approach considers learning from multiple perspectives.

1 DBN Structure and Principles

1.1 DBN Structure

In 2006, Hinton proposed a probabilistic generative model for deep neural networks: the deep belief network. By training the weights between neurons, it generates training data according to maximum probability.

DBN is a deep network obtained by stacking multiple restricted Boltzmann machines (RBM), training the DBN by training multiple layers of RBMs. The model consists of two parts: a visible layer and a hidden layer. Each neuron in the hidden layer continuously trains through RBM to mine deep relationships in the data, namely deep-level features. As shown in [Figure 1: see original paper], during each layer' s training, the data vector is first used to obtain the hidden layer quantity, which is then used as input data for the next (higher) layer. This method of learning information through layer-by-layer progression is called the greedy layer-wise algorithm. The bottom layer represents the raw data vector, with each neuron in the bottom layer representing one dimension of the input data.

1.2 RBM Principle

The training process of RBM is essentially finding a probability distribution that generates training samples. It reconstructs input signals as much as possible through input signals and hidden layer features, characterized by an energy function as shown in equation (1).

1111()nmmnijijjjiiijjivhwhvbvchE , |{w,b,c} ijw

The purpose of training RBM is to minimize the energy function. Based on the above analysis, we can obtain the joint probability distribution of the RBM model as shown in equation (2).

(v,h)1(v|)=exp((v,h|))()hPEZ

where is a normalization constant representing the sum of all distributions, calculated as shown in equation (3).

()Z (v,h)(v,h|),()EvhZe

When the input is fixed, the probability distribution of the j-th hidden layer node is as shown in equation (4).

(1|,)()vjjiijjPhgbvw

When the hidden layer nodes are determined, the distribution of the i-th reconstructed signal is as shown in equation (5).

(1|,)()iijijjPhgvchw

1.3 DBN Training Process

a) Input a new data vector , initialize weights, and train the weight coefficients of the first layer RBM;

b) Use Gibbs sampling for data reconstruction and continuous learning, continuously updating the weights between layers through reconstruction errors;

c) Train the DBN using an unsupervised layer-wise greedy training method, using the output of the first layer RBM as the input of the second layer RBM, recursively calculating the hidden vector and weight coefficient matrix of each layer;

d) Add the label set of the original data to the output layer at the top of the model, and use the BP (error back propagation) algorithm to fine-tune the entire network, making the connection weights of each layer as optimal as possible to output classification results.

1.4 Influence of Algorithm Parameters

During training, adding each network layer or increasing the number of nodes in each layer adds more and deeper learning links, improving learning effects and getting closer to the true expression of data. However, excessive increases in network layers and node numbers make the structure complex and increase computational load, which instead reduces algorithm efficiency and accuracy. In the DBN model learning process, the learning rate value directly affects algorithm efficiency. If the learning rate is too small, training convergence becomes too slow; conversely, it will cause the cost function to oscillate and fail to converge.

2 Signal Sorting Based on Stacking DBN

2.1 Stacking DBN Process

Using multi-level DBN models can obtain different prediction results, overcoming the problems of insufficient learning capability and inadequate network structure design of single models, learning more comprehensive essential features, and thus obtaining more accurate classification results. The basic structure is shown in [Figure 2: see original paper].

The basic steps are as follows:

a) First, divide the research dataset into training and test sets according to a certain proportion. Through multiple DBN models (with node numbers of 100/200/300 per layer), conduct different levels of in-depth learning on signals, and transform the learning results into basic probabilities through the SoftMax method;

b) For the training set, establish a stacked generalization learning framework through multiple deep learning models to form the Stacking DBN model in this paper;

c) Conduct learning prediction on new data (test set) using the trained stacked deep model, outputting the classification probability of each input;

d) Then comprehensively combine the results for final decision discrimination and output the results.

where the input X refers to the spectral variation feature values of radar signal samples in this paper, and Y is the true label of each input sample, i.e., the category number of the signal belonging to a certain radar.

The final classification decision is made by learning the posterior probabilities of different models.

2.2 Signal Sorting Process

The radar emitter signal sorting and recognition process based on the improved stacked DBN model in this paper is shown in [Figure 3: see original paper].

First, the radar time-series signals are preprocessed. FFT is applied to obtain basic frequency domain information, i.e., spectral waveform distribution features, as the input X for the deep model training network. Then, training and learning of multi-layer models are conducted according to the method in [Figure 2: see original paper] to obtain the classification posterior probabilities of multi-layer DBNs and perform linear fusion. Finally, SVM with strong generalization capability is used as the classification decision layer to obtain the final classification results.

3 Radar Emitter Signal Sorting

The essence of signal sorting and recognition is the process of separating pulse sequences belonging to single radar emitters from the pulse flow received by the receiver, with the basic process shown in [Figure 4: see original paper].

3.1 Radar Signal Feature Analysis

Radar signal sorting is mainly achieved based on the similarity and difference patterns among parameters of mixed radar signals. Parameters characterizing signal features mainly include frequency domain parameters (carrier frequency, spectrum, frequency variation patterns, etc.), spatial domain parameters (signal direction of arrival, azimuth angle, etc.), time domain parameters (pulse arrival time, pulse width, pulse variation patterns), as well as time-frequency domain and wavelet transform domain features.

3.2 Data Description

The experimental data used in this paper comes from radar simulation monitoring data provided by a key laboratory. The parameters of the studied radar signal types are all set with reference to parameters of radars already in service.

In the data simulation experiment, the first type of radar signal has a carrier frequency of 9500 MHz, pulse width of 1.2 µs, and PRI jitter range of 1656~1750 µs. The second type of radar has a carrier frequency of 9682 MHz with fixed pulse width of 8 µs. The third type of radar has a carrier frequency of 9540 MHz and pulse width of 0.5 µs. The fourth type of radar has a carrier frequency of 9530 MHz, fixed pulse width of 0.5 µs. The fifth type of radar uses six frequency points for group-varying linear frequency modulation: 9513 MHz, 9518 MHz, 9523 MHz, 9548 MHz, 9553 MHz, and 9563 MHz, with pulse widths in groups of 3~5, each group fixed at values of 6 µs, 12 µs, or 18 µs. The sixth type of radar uses frequency points 9612 MHz, 9618 MHz, 9624 MHz, 9648 MHz, 9553 MHz, and 9654 MHz for group-varying linear frequency modulation, with values of 25 µs, 32 µs, or 50 µs. The seventh type of radar has carrier frequency 9500~9700 MHz, pulse width 1.1 µs, and fixed PRI of 1269 µs.

4 Experiments

4.1 Data Preprocessing

Due to the complexity of the actual electromagnetic environment and limitations of signal receivers, received pulses may contain missing pulses and false pulses, among other uncertainties. To address the problem of inconsistent pulse dimensions, the simulated radar pulse lengths are screened to remove overly long and overly short pulse sequences. Each radar obtains 400 signal samples through sampling, and FFT transformation is performed as data augmentation to obtain spectral waveform information features as input vectors for the deep network.

4.2 Parameter Selection

The DBN selects a multi-hidden-layer structure. With unsupervised learning process rate and supervised learning rate both initially set to 1 and the activation function set to Sigmoid, we study the influence of other important parameters on the algorithm.

4.2.1 Number of Hidden Layers With the number of nodes per layer set to 100, we study the effect of different network layers by changing the number of training epochs. The experimental results are shown in [Figure 5: see original paper].

From the experiments, we can see that as the number of training epochs increases, networks with different numbers of hidden layers become more computationally complex, and their classification performance shows a slow downward trend overall. For the simulation signals in this paper, the DBN algorithm with 2 hidden layers can achieve relatively good classification performance with fewer training epochs.

4.2.2 Influence of Learning Rate on Classification Performance Based on the above experimental results, we study the influence of different numbers of hidden layer nodes on signal classification performance, with results shown in [Figure 6: see original paper].

From the experiments, we can see that for the simulation signals in this paper, as the number of hidden layer nodes continuously increases, the structure becomes more complex and unstable, and classification performance shows an overall trend of first increasing and then slowly decreasing, achieving the highest classification accuracy when the number of nodes is 120, with an overall average recognition rate above 93%.

With reference to relevant literature and empirical values, the deep belief network structure can be set as follows: DBN selects a two-hidden-layer structure with the number of nodes per layer set to 120. We study the influence of learning rate factors in the unsupervised and supervised learning processes, with experimental results shown in [Figure 7: see original paper].

From the experiments, we can see that R1 has stable values in the relatively small range of 0~0.36, while R2 can achieve relatively high accuracy at 0.5. As the learning rate increases, it will cause the cost function to oscillate and fail to converge. Therefore, in practice, reasonable values are generally selected through experimental verification.

4.2.3 Influence of Stacked Model Layers on Classification Performance Setting the basic DBN model structure as two hidden layers with 120 nodes per hidden layer, and based on the above experiments, we study the influence of the number of stacked model layers in the proposed algorithm on classification results, with experimental results shown in [Figure 8: see original paper].

From the above experiments, we can see that for the spectral distribution features of the simulated radar signals, when the Stacking DBN model reaches 4 stacked layers, it achieves the best classification effect with accuracy above 97%. However, as the number of stacked layers continues to increase, the model structure becomes more complex, and the learned signal features may contain errors and redundancy, so the accuracy decreases.

4.3 Performance Comparison of Different Classification Methods

Experiments were conducted to compare and analyze the performance of different classification methods. The SAE method is a model formed by stacking multiple autoencoders, which can learn features in datasets and has strong robustness and feature expression capability. The SVM classifier is currently a method with strong generalization capability in pattern recognition and classification. The latter method is a signal classification method based on pulse description word features, which is time-consuming in feature extraction and constrained by prior knowledge.

For the seven different types of radar signals simulated in this paper, the frequency domain waveform distribution features obtained through FFT transformation are used as experimental data. Referring to relevant literature, other algorithms are compared. The SAE deep model method selects optimal parameters through experiments for radar signal recognition. The SVM classification method obtains optimal parameters through 5-fold cross-validation and grid search experiments for signal classification. The experimental results are shown in .

** Performance Comparison of Different Signal Sorting Methods**

Classification Method	Accuracy/%
Our Algorithm	97.25
DBN	93.5
PDW+SVM	-

From Table 1, we can see that for the simulated radar signals, the DBN method can achieve 93.5% accuracy, while the improved Stacking DBN method proposed in this paper achieves a higher accuracy of 97.25%, which is about 7% higher than the stacked autoencoder SAE method, about 9% higher than the method using SVM directly on frequency domain features, and about 5% higher than the classification method based on pulse description word features. This indicates that the proposed method can extract more sufficient and comprehensive essential features through multi-layer network feature learning, thereby effectively improving classification performance.

5 Conclusion

Starting from the frequency domain waveform distribution features of radar signals, this paper combines a multi-level deep belief network improved model to conduct more comprehensive and automatic learning of deep-level features, and explores the influence of DBN' s hidden layer parameters, iteration numbers, and learning rates on signal classification to optimize and simplify the network structure. Secondly, by fusing the prediction results of multiple deep learning models for decision analysis, ideal classification results are achieved, with classification accuracy higher than other classification methods.

References

[1] Salakhutdinov R, Hinton G E. Deep Boltzmann machines [C]// Proc of the 12th International Conference on Artificial Intelligence and Statistics. 2009:
[2] 张葛祥, 荣海娜, 金炜东. 基于小波包变换和特征选择的雷达辐射源信号识别 [J]. 电路与系统学报, 2006, 11 (6): 45-49.
[3] Zhou Zhiwen, Huang Gaoming, Gao Jun, et al. A deep learning algorithm for radar emitter recognition [J]. Journal of Xi' an Electronic and Science University, 2017, 44 (3): 85-90.
[4] 余志斌. 基于脉内特征的雷达辐射源信号识别研究 [D]. 成都: 西南交通大学, 2010.
[5] Sarikya R, Hinton G, Deoras A. Application of deep belief networks for natural language understanding [J]. IEEE Transon Audio, Speech, and Language Processing, 2014, 22 (4): 778-784.
[6] Jurgen S. Deep learning in neural networks: an overview [J]. Neural Networks, 2015, 61: 85-117.
[7] Welling M, Hinton G E. A new learning algorithm for mean field Boltzmann machines [C]// Proc of International Conference on Artificial Neural Networks. 2002: 351-357.
[8] Hinton G, Salakhutdinov R. Reducing the dimensionality of data with Neural Networks [J]. Science, 2006, 313 (5786): 504-507.
[9] Bengio Y, Lamblin P, Popovici D. Greed layer-wise training of deep networks [J]. Advances in Neural Information Processing Systems, 2007, 19:
[10] Hinton G. Deep neural networks for acoustic modeling in speech recognition: the shared views of four research groups [J]. IEEE Signal Processing Magazine, 2012, 29 (6): 82-97.
[11] Qiu Xueheng, Zhang Le, Ponnuthurai N, et al. Ensemble deep learning for regression and time series forecasting [C]// Proc of IEEE Symposium on Computational Intelligence in Ensemble Learning. 2014: 122-126.
[12] Deng Li, Yu Dong, Platt J. Scalable stacking and learning for building deep architectures [C]// Proc of IEEE International Conference on Acoustics, Speech and Signal Processing. 2012.
[13] Sun Zhijun, Xue Lei, Xu Yang. Feature extraction algorithm for marginal Fisher analysis based on deep learning [J]. Journal of Electronics and Information, 2013, 35 (4): 805-811.
[14] Chamasemani F F, Singh Y P. Multi-class support vector machine (SVM) classifiers-an application in bioinspired computing: theories and applications (BIC-TA) [C]// Proc of the 6th International Conference on Bio-Inspired Computing: Theories and Applications. 2011.
[15] Mohamed A, Dahl G E, Hinton G. Acoustic modeling using deep belief networks [J]. IEEE Trans on Audio, Speech and Language Processing, 2012, 20: 14-22.

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