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Abstract

To improve radar target recognition accuracy, a High-Resolution Range Profile (HRRP) recognition method based on Deep Belief Network (DBN) is proposed. First, Restricted Boltzmann Machine (RBM) is employed for layer-wise unsupervised training of HRRP data, network parameters are updated according to the Contrastive Divergence (CD) algorithm, the DBN depth is designed through error reconstruction, then the DBN model parameters undergo supervised fine-tuning using the Backpropagation (BP) mechanism, and finally HRRP classification and recognition are achieved based on this model. Experimental results demonstrate that, compared with traditional neural networks, the recognition accuracy and noise robustness of the Deep Belief Network designed in this paper are significantly improved, with recognition accuracy increased by 8.5%.

Full Text

Preamble

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High-Resolution Radar Range Profile Recognition Based on Deep Belief Network

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Abstract: To improve radar target recognition accuracy, this paper proposes a high-resolution range profile (HRRP) recognition method based on deep be-

lief network (DBN). The method first employs restricted Boltzmann machines (RBMs) to perform layer-by-layer unsupervised training on HRRP data, updating network parameters via the contrastive divergence (CD) algorithm and determining DBN depth through reconstruction error design. Subsequently, the DBN model parameters are fine-tuned via supervised back-propagation (BP). Finally, HRRP classification and recognition are realized based on this model. Experimental results demonstrate that compared with traditional neural networks, the proposed DBN-based approach significantly improves recognition accuracy and noise robustness, achieving an 8.5% increase in recognition accuracy.

Keywords: deep belief network; high resolution range profile; reconstruction error; target recognition

0 Introduction

Radar target recognition and classification represent key technologies in fourth-generation radar systems and constitute a major research focus in contemporary radar development. High-resolution range profile (HRRP) is the one-dimensional projection of a target' s three-dimensional structure, effectively reflecting the distribution of target scattering centers along the radar line of sight (RLOS). HRRP provides more feature information than low-resolution radar target echo signals while avoiding the complex motion compensation and excessive computational time required for two-dimensional or three-dimensional imaging, offering unique advantages in terms of acquisition convenience and processing efficiency. Consequently, HRRP-based target recognition has become a significant research direction in radar automatic target recognition (RATR).

Current HRRP recognition methods primarily include template matching, support vector machines, clustering, principal component analysis, sparse representation, and neural networks. However, these approaches require manual feature extraction during data preprocessing, exhibit limited capability in representing complex functions, suffer from low generalization ability, inevitably incur information loss, and frequently encounter challenges such as the curse of dimensionality, local optima, and overfitting, which hinder improvements in recognition accuracy.

To address issues inherent in traditional neural networks—including the need for large labeled datasets, slow convergence, and susceptibility to local optima —Hinton et al. proposed an unsupervised layer-wise greedy training method in 2006 that mitigates the "gradient vanishing" problem associated with increasing network depth, significantly enhancing classification and prediction accuracy and enabling neural network architectures to achieve greater scale and precision.

This paper presents a high-resolution radar target detection method based on deep belief networks. Through supervised and unsupervised training processes, the DBN model parameters are optimized. A method for determining the depth

of hidden layers based on RBM reconstruction error is designed, enabling the network to self-organize its training through computation and develop a network depth that satisfies accuracy requirements while minimizing computational cost. Experimental simulations validate the effectiveness of the proposed model.

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1 Deep Belief Network Model

A deep belief network (DBN) consists of multiple restricted Boltzmann machines (RBMs) stacked with a back-propagation (BP) network. Its training process comprises two phases: unsupervised pre-training and supervised fine-tuning. First, each RBM layer is pre-trained using unsupervised learning methods, with the output of lower-level RBMs serving as input to higher-level RBMs. Each RBM is trained greedily, and the contrastive divergence (CD) fast algorithm initializes RBM weights and biases to ensure optimal feature vector mapping. Subsequently, the trained RBMs are connected to a BP neural network, which supervises the fine-tuning of the DBN through the BP algorithm. The error function between the top-layer output and the desired output enables backpropagation-based fine-tuning of weights and biases throughout the entire network, optimizing DBN parameters. The architecture is illustrated in [Figure 1: see original paper].

1.1 Restricted Boltzmann Machine

A restricted Boltzmann machine is a typical energy-based model (EBM) constructed from two layers of neurons: a visible layer (the data input layer), typically Bernoulli or Gaussian distributed, and a hidden layer (the feature extraction layer), typically Bernoulli distributed. RBM neurons are fully connected bidirectionally between layers but have no intra-layer connections. Input data propagates from the visible layer to the hidden layer and then back to the visible layer, as shown in [Figure 2: see original paper].

Bernoulli-Bernoulli RBMs employ binary representations for both visible and hidden layers as binary variables. However, radar echoes are predominantly continuously distributed real-valued data, making binary variables inadequate for effective representation and causing a variable mismatch problem. Therefore, this paper adopts Gaussian-Bernoulli RBMs, replacing binary visible nodes with Gaussian real-valued variable nodes. The energy function for Gaussian-Bernoulli RBMs is:

$$E(v,h;\theta)=\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{w_{ij}}{\sigma_i}v_ih_j-\sum_{i=1}^{n}\frac{a_i}{\sigma_i^2}v_i-\sum_{j=1}^{m}b_jh_j+\sum_{i=1}^{n}\frac{v_i^2}{2\sigma_i^2}$$

where $\theta=(w_{ij},a_i,b_j)$, w_{ij} represents the connection weight between visible neuron v_i and hidden neuron h_j, a_i and b_j denote the bias values corresponding

to v_i and h_j, respectively, and σ_i is the standard deviation of the Gaussian noise for v_i.

From this energy function, the joint probability distribution of visible and hidden layer neurons is:

$$p(v, h; \theta) = \frac{e^{-E(v,h;\theta)}}{\sum_{v,h} e^{-E(v,h;\theta)}}$$

Since RBM neurons within the same layer are not connected, their activation states are independent. When the visible layer neuron states are given, the activation states of hidden layer neurons are mutually independent. The activation probability of the j-th hidden layer neuron is:

$$p(h_j = 1|v; \theta) = \sigma\left(\sum_{i=1}^{n} w_{ij} v_i + b_j\right)$$

Similarly, given the hidden layer neuron states, the activation probability of the i-th visible layer neuron is:

$$p(v_i = 1|h; \theta) = \mathcal{N}\left(\sum_{j=1}^{m} w_{ij} h_j + a_i, \sigma_i^2\right)$$

Maximum likelihood estimation enables training parameters to better fit the training data distribution. The RBM is trained iteratively using gradient descent algorithms. The parameter update formulas are:

$$\Delta w_{ij} = \eta\left(\langle v_i h_j\rangle_{\text{data}} - \langle v_i h_j\rangle_{\text{recon}}\right)$$

$$\Delta a_i = \eta\left(\langle v_i\rangle_{\text{data}} - \langle v_i\rangle_{\text{recon}}\right)$$

$$\Delta b_j = \eta\left(\langle h_j\rangle_{\text{data}} - \langle h_j\rangle_{\text{recon}}\right)$$

where η is the learning rate during the pre-training phase. When data dimensionality is high, computing model expectations via gradient descent becomes extremely difficult. The CD algorithm, similar to gradient descent, employs Gibbs sampling on reconstructed data to significantly accelerate RBM training. The mathematical expectations for the DBN model yield the following weight and bias update criteria:

$\langle\cdot\rangle_{\text{data}}$ represents the mathematical expectation of the training dataset

$\langle \cdot \rangle_{\text{recon}}$ represents the mathematical expectation of the reconstructed model

Through the unsupervised pre-training process described by these equations, RBM parameters can be adjusted to appropriate initial values, maximizing the avoidance of local optima.

1.2 Back Propagation Network

The BP neural network is a typical error backpropagation mechanism that classifies feature vectors from the RBM pre-training phase and fine-tunes DBN model weights and biases. The typical structure of a BP neural network is shown in [Figure 3: see original paper].

The backpropagation algorithm divides the network learning process into two phases: (a) forward signal propagation, where input signals are processed layer-by-layer through the input, hidden, and output layers to compute the actual output value of each unit; and (b) error backpropagation, where if a discrepancy exists between actual and desired outputs, the error signal is returned along the original connection paths, with the error distributed to all units in each layer to adjust neuron weights. These two processes are repeated iteratively until the network error meets requirements.

Assuming d_k and y_k represent the desired and actual outputs of the k-th output layer neuron, respectively, the residual term for the node is:

$$\delta_k = (d_k - y_k) \cdot y_k \cdot (1 - y_k)$$

The error backpropagation expression for the l-th layer neuron j is:

$$\delta_j^l = \left(\sum_{k=1}^{m} w_{jk}^{l+1} \delta_k^{l+1} \right) \cdot h_j^l \cdot (1 - h_j^l)$$

According to the gradient descent method, the weights and biases of the network during the fine-tuning phase are updated as follows, where ε is the learning rate during the fine-tuning phase:

$$w_{ij}^l \leftarrow w_{ij}^l + \Delta w_{ij}^l = w_{ij}^l + \varepsilon \cdot \delta_j^l \cdot y_i^{l-1}$$

$$b_j^l \leftarrow b_j^l + \Delta b_j^l = b_j^l + \varepsilon \cdot \delta_j^l$$

2 Network Architecture Design

2.1 Network Depth Design

Different network depths exhibit varying recognition performance and training time characteristics. Specifically: DBN training accuracy improves with increasing network depth; DBN computational performance decreases with increasing network depth; and DBN recognition efficiency remains essentially unchanged once top-layer units reach a threshold.

During DBN model training, network weights are already positioned relatively optimally through RBM unsupervised pre-training, with BP network fine-tuning adjusting weights only within a small range. Therefore, selecting an appropriate number of RBM hidden layers is crucial for model optimization. To satisfy training accuracy while minimizing computational cost, this paper designs the number of hidden layers based on the reconstruction error method, evaluating the difference between data reconstructed after one Gibbs sampling pass through the RBM and the original data:

$$\text{error} = \frac{1}{n \cdot m} \sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - R_{ij})^2$$

where error denotes reconstruction error, x_{ij} represents initial data, R_{ij} denotes network-reconstructed data, p defines the value range, L represents the number of RBM layers, and e is the expected error. The DBN depth is determined by comparing reconstruction error with expected error according to the following rule:

$$\begin{cases} L_{c+1} = L_c + 1, & \text{if error} > e \\ L_c = L, & \text{if error} < e \end{cases}$$

If the RBM reconstruction error meets the expected accuracy requirement during the pre-training phase, the network proceeds to the backpropagation fine-tuning phase. If not, an additional RBM layer is added and pre-training continues until the reconstruction error satisfies the requirement, thereby selecting an appropriate DBN depth. The network training flowchart is shown in [Figure 4: see original paper].

2.2 Hidden Layer Node Design

Increasing network depth and node count can reduce network error and improve accuracy, but also increases network complexity. Currently, no comprehensive theoretical basis exists for determining DBN node counts. This paper establishes network node counts through experimental methods.

The DBN model is designed with one RBM input layer, L RBM hidden layers, and one BP output layer. For simplicity, the number of nodes in each DBN

hidden layer is set to be identical. For different hidden layer node counts, network models are designed according to the reconstruction error method and compared through testing, with results shown in .

Analysis reveals that DBN reconstruction error precision is closely related to both network node count and depth. When the hidden layer contains more nodes, only a few RBM layers are needed to meet reconstruction error targets and achieve high recognition rates. When the hidden layer contains fewer nodes, more hidden layers must be added to reach the target error. Training time also increases with network depth and node count.

Experimental results indicate that setting hidden layer nodes to 64 yields optimal DBN classification accuracy, with the reconstruction error method determining that 2 hidden layers are optimal for the network.

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3 Experiments and Analysis

The experiments utilize measured radar echo data from four types of off-road vehicles, with 1,280 range profiles collected for each target type. Each range profile has a length of 256, as shown in [Figure 5: see original paper]. Sixty percent of the total data is selected as the training set, with the remaining 40% used as the test set.

Based on reference [27], DBN parameters are set using grid search optimization as follows: learning rates of 0.1 for both pre-training and fine-tuning phases, a minimum batch size of 32, and 20 iterations (as samples stabilize after 20 iterations). The input layer contains 256 nodes, and the output layer contains 4 nodes. The network architecture is designed as 256-64-64-4. After multiple experiments, the target expected error for reconstruction is set to 0.5, yielding optimal network performance, as shown in .

3.2 DBN Depth Impact Analysis

To validate the effectiveness of the DBN model designed using the reconstruction error method, comparative tests were conducted on DBNs with hidden layer node count of 64 but varying depths, as shown in .

The results demonstrate that as network depth increases, reconstruction error gradually decreases while computational time increases. When the hidden layer depth is 2, DBN recognition rate reaches its maximum at 99.8535% with a training time of 4.363 seconds. Continuing to increase network depth further reduces reconstruction error but leads to gradually decreasing recognition rates and severe overfitting. This confirms that the network design and parameter selection based on the reconstruction error method are accurate and effective.

The reasons for decreasing recognition rates with additional hidden layers are analyzed as follows: (a) increasing hidden layer count only reduces RBM re-

construction error during pre-training but cannot reduce network error during the BP fine-tuning phase; (b) additional hidden layers cause excessive accumulation of backpropagated error during fine-tuning; (c) increased hidden layer count reduces DBN generalization performance, leading to overfitting; and (d) additional hidden layers increase algorithmic time complexity and reduce efficiency.

3.3 Comparison with Other Classification Methods

To verify DBN recognition effectiveness and network stability for HRRP, deep belief networks are compared with traditional neural networks (NN), support vector machines (SVM), and convolutional neural networks (CNN). The NN employs BP optimization, SVM uses radial basis function kernels with parameters selected according to reference [6], and CNN adopts a one-dimensional structure (as reference [16] indicates this is optimal for HRRP, since converting one-dimensional range profiles to two-dimensional images destroys internal structural information). Comparative experiments were conducted on HRRP data with added Gaussian white noise at SNR = 3 dB, with recognition results shown in .

Experimental results demonstrate that under identical data conditions, DBN improves model recognition accuracy by 8.52% compared to NN, as RBM unsupervised pre-training provides appropriate initial values. Relative to SVM, DBN achieves a 5.49% accuracy improvement by leveraging multi-layer architecture to learn deep abstract data features. These results show that DBN, combining unsupervised and supervised learning characteristics, achieves superior classification performance compared to traditional algorithms. As shown in , DBN and CNN achieve similar recognition efficiency, but DBN reduces computational time by 40.3%. Due to internal convolutional pooling characteristics, CNN network operations are more complex and better suited for extracting two-dimensional image features, whereas DBN offers more pronounced advantages for processing HRRP data. After adding Gaussian white noise at SNR = 3 dB, the recognition rate remains at 98.12%, significantly higher than other networks, demonstrating robust noise resistance of the DBN architecture.

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4 Conclusion

This paper proposes a target recognition method for radar high-resolution range profiles based on deep belief networks. The DBN model is optimized through RBM unsupervised pre-training and BP supervised fine-tuning, with DBN hidden layer depth designed based on the reconstruction error method. Validation using measured data demonstrates that this method achieves 99.85% recognition accuracy in radar target classification experiments without requiring manual feature extraction, representing a substantial improvement over other classification algorithms with excellent network robustness. These results confirm the

application value of deep belief networks for HRRP recognition.

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