Postprint: Defect and Texture Recognition of Solid Wood Panels Using Deep Belief Networks

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Abstract

To address the requirement in modern wood processing enterprises where defects and texture serve as the primary quality grading elements for solid wood panels, a deep learning algorithm combining Local Binary Patterns, self-learning Deep Belief Networks, and a Softmax classifier is proposed to classify defects and textures in solid wood panels. First, defect and texture features are extracted from solid wood panels. Based on these features, Deep Belief Networks are utilized to train and learn from locally binarized features, while a self-learning learning rate algorithm is employed to optimize convergence speed and reduce training time. Finally, a Softmax classifier is used to obtain classification results for common defects as well as straight grain and decorative grain. Compared with several classical algorithms such as BP neural networks, Support Vector Machines, and Extreme Learning Machines, the Deep Belief Network approach achieves an error rate of approximately 3.59% for solid wood panel defect and texture recognition, demonstrating superior recognition performance for solid wood panel defects and textures.

Full Text

Preamble

Research on Defects and Textures Recognition of Solid Wood Lumbers Based on Deep Belief Network

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Abstract: In modern wood processing enterprises, the main quality classification factors for solid wood lumbers are defects and textures. This research proposes a deep learning algorithm that combines local binary patterns, self-learning deep belief networks, and a Softmax classifier to classify solid wood lumber defects and textures. First, defect and texture features of solid wood lumbers are extracted. Based on this, deep belief networks are used to train and learn the characteristics of locally binarized features, while a self-learning learning rate algorithm is adopted to optimize convergence speed and reduce training time. Finally, a Softmax classifier is employed to obtain classification results for common defects as well as straight and decorative grain patterns. Compared with several classical algorithms including BP neural networks, support vector machines, and extreme learning machines, the proposed deep belief network approach achieves an error rate of approximately 3.59% for solid wood lumber defect and texture recognition, demonstrating superior recognition performance.

Keywords: defect recognition; texture recognition; deep belief network; self-learning; local binary pattern

0 Introduction

Since Hinton proposed deep learning in 2006, it has achieved tremendous breakthroughs in speech [1], image [2], video [3], and text [4] processing domains. The concept of deep learning emerged in contrast to traditional shallow learning algorithms, simulating the human brain' s analytical process by combining and learning from low-level data to form more abstract high-level feature representations (categories, attributes, etc.), thereby improving feature recognition and classification accuracy. Traditional shallow learning structures such as support vector machines, maximum entropy models, and hidden Markov models merely transform raw input data into a specific problem space, forming some simple feature structure that is easy to process [5]. These shallow learning structures have limited representation capabilities for complex problems when dealing with constrained samples and computational resources, and exhibit poor generalization.

In contrast, deep learning can approximate complex functions nonlinearly, represent the distributed representation of input data, and demonstrate powerful capabilities for learning the essential features of datasets from massive samples [6]. In image recognition, the most typical application of deep learning is in handwritten digit dataset (MNIST) recognition, where error rates have been reduced to 1.2%. In 2012, Krizhevsky combined deep learning with convolutional neural networks in the ImageNet Large Scale Visual Recognition Challenge, designing the AlexNet deep network model that reduced recognition error rates to 15.32%, far below the 26.2% error rate achieved by the second-place traditional method. By 2014, participants had optimized and improved upon Krizhevsky' s network structure, designing GoogLeNet, which successfully reduced the recognition error rate to 6.66%. In 2015, the ResNet network structure achieved a 3.57% error rate, surpassing human recognition error rate of 5.00%. By 2017, the error rate had dropped to as low as 2.25%. Figure 1 [Figure 1: see original paper] illustrates the recognition error rates from the ImageNet competition between 2010 and 2017.

In wood processing production, wood defects significantly impact wood quality, which in turn determines the commercial and use value of wood and its products. The comprehensive utilization rate of domestic raw wood materials in China is very low at only 63%, far below the average rate of over 80% in developed countries, with low efficiency in wood defect detection being one of the main reasons [7]. In recent years, numerous scholars have researched and proposed wood defect detection methods to improve the comprehensive utilization rate of wood raw materials [8], including quantitative analysis of wood defects based on 3D scanning technology [9], wood defect detection using drilling resistance methods [10], and wood defect recognition based on fast l1 algorithms and LBP algorithms [11]. These methods suffer from various limitations such as high equipment costs, stringent requirements for actual detection work environments, and inability to achieve large-scale industrial application. In contrast, machine vision-based wood defect detection technology can reduce subjective factors in the recognition process, eliminate dependence on specific detection equipment, and has relatively low environmental requirements, making it the preferred detection technology.

Traditional machine vision technologies are mostly based on shallow learning algorithms, which often require cumbersome processing procedures such as image preprocessing, threshold segmentation, feature extraction, pattern recognition, and edge detection when identifying wood defects, yet still fail to achieve satisfactory recognition accuracy [12]. This creates significant difficulties for detecting complex wood texture information. Based on these considerations, this paper applies deep learning-based deep belief networks to wood defect and texture recognition, incorporating LBP feature extraction and a self-learning step size method to optimize the feature learning process and reduce algorithm training time.

1 Deep Belief Network

Geoffrey Hinton proposed the deep learning model known as Deep Belief Networks (DBN) in 2006, whose fast greedy layer-wise unsupervised training algorithm serves a dimensionality reduction role in multi-layer neural networks [13]. DBN is a deep learning model that combines unsupervised and supervised learning, composed of several layers of Restricted Boltzmann Machines (RBM) and backpropagation fine-tuning algorithms, capable of extracting deep structural feature information from training data.

1.1 Restricted Boltzmann Machine

The Boltzmann Machine (BM) is a generative stochastic fully-connected neural network with symmetric connections and no self-feedback, belonging to the category of auto-encoder networks. It possesses powerful unsupervised learning capabilities and can learn complex rules from datasets. However, its training time is long and it is difficult to obtain its probability distribution. To overcome this limitation, Smolensky introduced the Restricted Boltzmann Machine (RBM), which consists of some visible units (corresponding to visible variables) and some hidden units (corresponding to hidden variables). Both visible units v and hidden units h are binary variables, meaning their states take values of 0 or 1. The entire network is a bipartite graph where edges exist only between visible units and hidden units, with no connections between visible units themselves or between hidden units themselves. Figure 2 [Figure 2: see original paper] shows the network structures of BM and RBM.

RBM is an Energy-Based Model (EBM). According to the EBM description of a random system, energy fluctuations in the system are related to the degree of order in the system. More ordered systems have smaller energy fluctuations and tend toward equilibrium, while more disordered systems have larger energy fluctuations and tend toward disequilibrium. For a given set of states (v, h), the joint configuration energy function of its visible units v and hidden units h is:

$$E(v,h|\theta) = -\sum_i b_i v_i - \sum_j c_j h_j - \sum_i \sum_j v_i W_{ij} h_j$$

where $\theta = \{W_{ij}, b_i, c_j\}$ represents the RBM parameters, W_{ij} is the weight of the edge between visible unit v and hidden unit h, b_i is the bias of visible unit v, and c_j is the bias of hidden unit h. Based on this energy configuration function, the joint probability of (v, h) is:

$$P_\theta(v,h) = \frac{\exp(-E(v,h|\theta))}{Z(\theta)}$$

where $Z(\theta) = \sum_{v,h} \exp(-E(v,h|\theta))$ is the normalization factor, also known as the partition function.

Due to the conditional independence between visible units v and hidden units h, and the symmetric structure of the RBM model, when the states of visible units v_i are given, the activation probability of the j-th hidden unit is:

$$P(h_j = 1|v) = \sigma\left(c_j + \sum_i W_{ij} v_i\right)$$

where $\sigma(x) = \frac{1}{1+\exp(-x)}$.

Similarly, when the states of hidden units h_j are given, the activation probability of the i-th visible unit is:

$$P(v_i = 1|h) = \sigma\left(b_i + \sum_j W_{ij}h_j\right)$$

Taking the partial derivative of the log-likelihood probability of visible units v with respect to W_{ij}, we obtain the RBM weight update rule:

$$\Delta W_{ij} = \varepsilon\left(\langle v_i h_j\rangle_{\text{data}} - \langle v_i h_j\rangle_{\text{model}}\right)$$

where ε is the weight learning rate, $\langle v_i h_j\rangle_{\text{data}}$ is the expectation under the data distribution, and $\langle v_i h_j\rangle_{\text{model}}$ is the expectation defined by the RBM model. Using the Contrastive Divergence (CD) algorithm, we can obtain an approximate probability distribution through Gibbs sampling to estimate the required probability distribution, yielding an approximate value for $\langle v_i h_j\rangle_{\text{model}}$ to complete the weight update.

Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method. For a random vector $X = (X_1, X_2, \dots, X_K)$ of length K, assuming we cannot obtain the joint distribution $P(X)$, but can obtain the conditional distribution $P(X_K|X_{K-})$ of the K-th component given the other components, where $X_{K-} = (X_1, X_2, \dots, X_{K-1}, X_{K+1}, \dots, X_K)$. Starting from an arbitrary state of X, we iteratively sample each component in sequence using its conditional distribution. As the number of sampling iterations increases, the probability distribution of the random variable $X^{(n)} = (X_1^{(n)}, X_2^{(n)}, \dots, X_K^{(n)})$ converges geometrically to the joint probability distribution $P(X)$.

1.2 Deep Belief Network Structure and Learning Process

DBN is a deep neural network model containing multiple hidden layers. The DBN used in this paper is shown in Figure 3 [Figure 3: see original paper], consisting of four RBMs. Input data undergoes unsupervised pre-training as the visible layer of the first RBM, then the input representation obtained from the first layer serves as the visible layer data for the second RBM. After passing through four RBMs, additional learning algorithms (such as BP neural networks) can be incorporated to convert the learned representations into supervised predictions, while comparing expected output labels with predicted output labels to fine-tune the weights. The DBN network structure designed by Professor Hinton in 2006 employs an unsupervised greedy layer-wise training method to train generative models, seeking optimal solutions at each training stage. Since greedy algorithms seek local optimal solutions, a global learning algorithm must be applied to fine-tune network parameters to obtain a global optimal solution.

2 Wood Defect Recognition Based on DBN

This paper proposes using a DBN constructed with four RBMs to recognize wood defects, with parameter fine-tuning performed using a single-layer BP neural network. To enable DBN to better process image information, Local Binary Pattern (LBP) is incorporated for feature extraction, a self-learning learning rate is adopted to optimize the training process, and a Softmax classifier is added to the final DBN layer to achieve feature classification.

2.1 LBP Processing of Wood Images

LBP can extract defect feature information and performs particularly well in texture feature extraction [14], making it suitable for extracting feature information from wood images. The LBP operator is limited to a 3×3 pixel range, using the pixel value at the center of the square as a reference to compare with peripheral pixel points. If a peripheral pixel value is larger than the center value, the current position is set to 1; otherwise, it is set to 0. This rule binarizes pixel values in local regions, simplifying data for subsequent image processing. To make the extracted features rotation-invariant [15], the LBP-selected local region is rotated to obtain multiple different binarized sequences, from which the smallest value is selected to represent the feature value. Additionally, a uniform LBP pattern is used, which requires that transitions from 0 to 1 or from 1 to 0 in the binary sequence occur no more than 2 times (with the binary sequence being circular). This approach reduces dimensionality and overcomes the problem of large frequency distribution differences appearing in rotated LBP patterns within an image. This paper utilizes this uniform LBP pattern to ensure image rotation invariance.

Figure 4 [Figure 4: see original paper] illustrates the local binarization process of the LBP operator. Figure 5 [Figure 5: see original paper] shows the effect of LBP processing on wood images, demonstrating effective feature information extraction. Figure 6 [Figure 6: see original paper] displays the histogram statistics of wood images after grayscale and LBP processing. Based on the LBP feature matrix in Figure 4, a binary string 11100111 can be obtained starting from the top-left corner in clockwise order. Converting this binary string to decimal yields an LBP value of $1 + 2 + 4 + 32 + 64 + 128 = 231$. Similarly, the LBP feature histogram of wood images can be statistically calculated.

2.2 Self-Learning Deep Belief Network Algorithm

The DBN network is trained layer-by-layer on RBM modules to obtain corresponding spatial parameters and construct the entire network architecture. The CD-based fast learning algorithm in RBM typically uses a global learning rate for network training. However, if the learning rate is too large, reconstruction error increases sharply and weights become abnormally large. If the learning rate is too small, these issues can be avoided but convergence becomes slow and training time increases. To resolve this contradiction, this paper introduces the concept of self-learning step size into the traditional DBN algorithm. During the iterative process of the CD fast algorithm, an independent step size parameter γ_{ij} (learning rate) is used for each connection weight W_{ij}, replacing the global learning rate in the original DBN network. The specific step size is adjusted according to factors including an increment factor u ($u > 1$) and a decrement factor d ($0 < d < 1$). If the weight update $\Delta W_{ij} > 0$, the step size is updated with $u\gamma_{ij}$; if $\Delta W_{ij} < 0$, the step size is updated with $d\gamma_{ij}$. During learning, to avoid conflicts caused by excessively large step sizes, the step size increases if a weight' s update direction remains the same for two consecutive iterations, and decreases otherwise.

2.3 Wood Defect Recognition Based on LBP and Self-Learning DBN

The specific process of wood defect recognition using LBP for feature extraction and self-learning DBN for classification is shown in Figure 7 [Figure 7: see original paper]:

a) **Data Preprocessing**: First, images are segmented into blocks according to the characteristics of the wood image database. Then, mean LBP processing is applied to each pixel within each block to obtain the LBP value for each pixel point. Next, histograms for each block are calculated and normalized. Finally, the histograms from each block are represented as feature vectors for processing by the self-learning DBN.

b) **Data Processing**: The obtained feature vectors are input into the self-learning DBN network. Deep information in the feature vectors is extracted from bottom to top. Using equations (3)–(5) and the self-learning learning rate update design, the spatial parameters $\{b_i, c_j, W_{ij}\}$ in the network structure are initially determined, after which the BP algorithm is used for parameter fine-tuning and optimization.

c) After the network is established layer-by-layer, a Softmax classifier is set at the output layer to classify the output data.

3 Recognition Results of Wood Defects and Textures Based on Self-Learning DBN

Original solid wood lumber images are processed using LBP to extract features and generate feature histograms. The data is normalized and input into the self-learning DBN network in the form of feature vectors. The DBN' s layer-by-layer learning capability is leveraged to train and learn from the data, with final classification performed through a Softmax classifier.

To verify the effectiveness of the proposed method, a network model was constructed using MATLAB 2017b Deep Learning Toolbox. The DBN consists of a main network framework of four RBMs and one Softmax classifier. The number of stochastic units in the input layer equals that in the visible layer of the first layer, with a size of $144 \times 96 = 13,824$ dimensions. The dimensions of the four hidden layers are designed as 1500, 500, 250, and 30, respectively. The final output dimension through the Softmax classifier is 8, corresponding to the number of classifier categories.

3.1 Wood Defect and Texture Recognition

The training dataset consists of 500 images sized 144 × 96, with 400 images used as training samples and 100 as test samples. Sample images are shown in Figure 8 [Figure 8: see original paper]. The defects in fir wood samples mainly include three types: knots, cracks, and holes, along with two primary textures: straight grain and decorative grain. By combining defects and textures, eight classification categories are obtained: knot+straight grain, knot+decorative grain, crack+straight grain, crack+decorative grain, hole+straight grain, hole+decorative grain, no defect+straight grain, and no defect+decorative grain, represented as k0–k7.

In the self-learning DBN network model designed in this paper, the increment and decrement factors are set to 1.2 and 0.8, respectively. During initialization, the learning rate for each DBN layer is set to 0.1. As the number of iterations increases, the advantages of the self-learning DBN network over the fixed learning rate DBN network become increasingly apparent, as shown in Figure 9 [Figure 9: see original paper]. The convergence performance of DBN networks is compared under self-learning rate, fixed learning rate of 0.1, fixed learning rate of 0.4, and fixed learning rate of 0.7. The results demonstrate that the self-learning rate DBN network outperforms fixed learning rate DBN networks. The DBN network learning rate should not be too large or too small. Increasing the learning rate accelerates network convergence, but an excessively large rate leads to network instability. Decreasing the learning rate makes the network more stable, but an excessively small rate results in slow convergence and easy trapping in local optima [16].

3.2 Comparison and Analysis of Recognition Rates Among Several Algorithms

To further validate the effectiveness of the classification algorithm, the proposed LBP + self-learning DBN + Softmax combination is compared with four other representative algorithms: Extreme Learning Machine (ELM) [17], Support Vector Machine (SVM) [18], Back Propagation (BP) [19], and Convolutional Neural Network (CNN) [20]. ELM and SVM are two widely used shallow learning algorithms. Here, ELM uses a single hidden-layer network with 1000 hidden nodes, combined with the AdaBoost algorithm to overcome output instability. The SVM algorithm uses a Gaussian kernel function, while the BP algorithm has only one hidden layer with 1000 nodes. CNN employs a 5-layer network structure including two convolutional layers, two max-pooling layers, and two fully connected layers, combined with a Softmax classifier. The specific classification recognition rates of each algorithm are compared in Table 1 . The comparison shows that the LBP + DBN + Softmax combination algorithm not only outperforms shallow learning algorithms but also demonstrates better recognition performance for solid wood lumber defects and textures than other deep learning algorithms.

Table 1: Comparison of Error Rates Among Different Image Classification Methods

Algorithm	Error Rate
AdaBoost + ELM	7.31%
SVM	8.77%
BP	10.60%
CNN + Softmax	5.42%
LBP + DBNs + Softmax	**3.59%**

4 Conclusion

The continuous improvement of non-destructive testing methods for solid wood lumber defects and textures aims to meet the needs of modern wood processing enterprises to improve product quality and reduce economic costs. This paper investigates the specific application of deep belief networks in wood defect and texture detection. LBP is used to process collected solid wood lumber images to obtain wood defect and texture information, which is converted into feature histograms and imported into the DBN model. A self-learning learning rate method is introduced into the DBN' s layer-by-layer RBM training, and a Softmax classifier is finally employed to achieve multi-classification of defect and texture features. On a solid wood lumber image dataset, 400 fir wood images are used as the training set and 100 images as the test set. Using MATLAB' s Deep Learning Toolbox and a GTX 1080Ti GPU, the algorithm training time is optimized and the algorithm' s effectiveness is verified. The proposed algorithm converges in approximately 400 iterations within 500ms, achieving a recognition error rate of 3.59%. Compared with ELM, SVM, BP, and CNN algorithms that cannot accurately recognize wood texture features, this algorithm achieves excellent classification results. However, when processing high-dimensional images with millions of pixels or more, the processing time and detection accuracy of this algorithm still need improvement. Future work will focus on optimizing the algorithm from these two aspects and extending the proposed solid wood lumber defect and texture detection method to complete solid wood lumber image defect and texture detection.

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Note: Figure translations are in progress. See original paper for figures.