A robust wood plank surface defect detection based on fuzzy logic

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Abstract

In this paper, a novel approach of image segmentation for wood surface defect detection based on neural-fuzzy logic is proposed. Automated quality control has become a staple of computer vision in the last decades since it is a task that is demanding for humans, high accuracy is difficult to achieve, and it has great potential to lower cost and speed up production. The focus of this study is to tackle the problem of reliable segmentation of wood planks and the classification of multiple defects. The wood surface visual database used in this study was acquired in association with the local wood manufacturing industry. It consists of 900 images of wood planks from the tree Picea abies, containing 18 categories of defects and 3 types of wood textures. Our method achieves an overall defect detection accuracy rate of 92.3 % with a low false-positive detection rate.

1. Introduction

In the last decades, a large variety of automated visual inspection (AVI) methods have been proposed, to achieve a reliable identification of wood surface defects. These methods can be broadly categorized as image-based classification, object detection, and segmentation. Lumber quality grading was proven to be a tedious task for humans, resulting in a less than optimal detection accuracy rate [1, 14, 20]. Automated detection based on computer vision, promises to solve this problem while speeding up manufacturing significantly.

Wood surface defects lower the value of the whole wood plank as they might cause structural weakness or limit their use in furniture manufacturing and veneers. In the industrial manufacture plant, the segmentation procedure is followed by the cutting of planks to remove the inadequate parts. Therefore, false-positive detection of defects is a considerable problem, as healthy units might be discarded, lowering the profit margins. One of the main goals of our algorithm is to minimize the ratio of false-positive detections, and consequently the discard ratio of healthy units.

Possible defects are tagged as one of the following 18 categories: healthy knot, healthy spike knot, dead knots, dead spike knot, hole, pith, bark pocket, rot and decay, bark or wane, worm holes, worm gallery, resin pockets, fiber damage, blue stain, brown stain, crack and splits, lack of material, and resin on the surface. Importantly, the production process may cause some abrasions or scratches on the surface of the planks. An additional requirement is the classification of the wood general texture as radial, semi radial, or tangential. Wood texture can affect the wood value and strength, so it should be sorted accordingly. It is important to note, that multiple textures can be present on a single plank.

A persistently troublesome task in wood surface segmentation is the detection of a discoloration called Blue stain, which is caused by microscopic fungi, and may occur as a blue, gray, or brown variant. Supposedly, Blue stain does not cause structural weakness of the wood but can lower the aesthetic value of the planks used as building, or furniture material. Other stains are also possible on the wood surface, which are sometimes confused for blue stain, i.e. chemical brown stain that is caused by drying, or lubricant oil from machinery. Additionally, any wobble of the passing plank as it moves by the fixed camera may cause an abrupt shift in the intensity of the measured color, further complicating the detection problem.

2. Related work

Since the input data from images can be very large, classification of defects usually relies on some emblematic features, whose extraction from the data is often a non-trivial task. Most algorithms involve some type of data filtering and augmentation, then indicative features are calculated, and finally, a classifier is trained. Image segmentation combines these steps, assigning a label directly to every pixel. An overview of the classically used methods is presented in [3]. This paper studied seven types of defects, including blue stain, for which the largest errors were observed. It encompasses results from methods using thresholding (Otsu, Kapur's entropy, transition-matrix), edge detection (compass gradient mask, Shiozaki's entropy), morphological operations, clustering, color space transformation. The most successful was the clustering method with region growing, while the thresholding and edge detection methods did not perform well for low contrast defects. Incidentally, stain and pitch streaks were described as subtle features, since they do not contrast well on gray-scale images, thus they require the use of color information. Furthermore, the color space transformation did not significantly improve the defect detections.

Notably, a neural-fuzzy approach of image segmentation, Fuzzy min-max neural network for image segmentation (FMMIS), was presented in [17]. This method uses hyperboxes as fuzzy sets and an expansion-contraction online learning algorithm. The categories of defects in this study mostly match ours, principally blue stain, and their method achieved a defect detection rate of 94.4%. The authors also noted, that the red channel performed best at separating defects from the background texture. Others [18],[19], also confirm this find.

A tree-structure support vector machine (SVM) was used in [4] to classify four types of wood knots, with an average classification rate of 96.5%. The features are defined as an average pseudo color using an order statistic filter (OSF). Firstly, the boundaries of the defects were estimated with an edge detection algorithm, and connected with a B-spline curve. Then, the image was filtered and a nonlinear L-estimator was used to normalize the observed colors. The authors noted that the defect image blue components had low contrast. Comparably, an SVM classification was used in [7]. A bag-of-words dictionary was created with K-means clustering of features acquired by local binary patterns (LBP) and the speeded-up-robust-feature (SURF) method. For classification, the input image was firstly preprocessed with contrast stretching transformation, before it was classified with an SVM. This method achieved a precision of 92% while mentioning blue stain detection as future work.

Authors in [2] used a convex optimization (CO) method as pretreatment smoothing, and Otsu thresholding, to classify four basic defects with an average accuracy rate of 94.1%. They used a structural similarity (SSIM) index to compare the filtered images. The classification was implemented with the classification and regression tree (CART).

In [23], a principal component analysis (PCA) method was used to reduce the dimensionality of features acquired by mathematical morphology, in conjunction with a compressed sensing classifier. In another study by the same authors [11], they used a SOM neural network with linear discriminant analysis (LDA) method, which reduces data dimensionality by maximization of the between-class variance to the within-class variance. In both of those studies the models were tested for three defect categories, resulting in a classification accuracy of 92%, and 94%, respectively.

Another method of feature extraction was presented in [1], using a Daubechies db2 discrete wavelet transformation (DWT). These features were then classified using K-nearest neighbors (KNN). Wavelet transforms are usually used as filters and for image compression. This study classified seven defect types, with an accuracy rate of defects of 98% by number found. Similarly, in [21], images were transformed using a Haar DWT. The transformation coefficients were normalized, transformed into binary values with a threshold, and clustered with an expanding seed based method. From this, the energies of the clusters were calculated and used as features. The best classification was done using a probabilistic neural network (PNN), with an overall accuracy of 87.0%.

By amalgamating multiple previously mentioned methods, a hybrid feature extraction using LBP, orders statistics, and gray level co-occurance matrix (GLCM), was presented in [13]. GLCM is a statistical measure of pixels spatial relationship, based on distance and orientation. Additionally, PCA and LDA were used for feature vector dimension reduction. For classification, the SVM and KNN methods were compared. Combined features from GLCM and LBP performed best, with an reported accuracy of 100%. Curiously, a neural network was trained with particle swarm optimization (PSO) and GLCM features [15], but it only achieved an accuracy of 78%.

A Law's texture energy measures (LAWS or LTEM) method was presented in [9]. This method is based on combinations of local kernel convolution, and is primarily used for texture feature extraction in the biomedical field. A feed-forward back propagation neural network was used as a classifier for five defect classes, with an accuracy rate of 90.4%. Another artificial neural network (ANN) based on PCA dimension reduction of feature descriptors [22] was used to classify 13 defect classes, with an accuracy rate of 92%. The neural network was trained using backpropagation. This study focused mainly on the identification of the most adequate ANN structure.

Wood-type identification is addressed using fluorescence spectroscopy in [14], since it provides better signal to noise ratio (SNR) than infra red (IR) measurements, which are affected by external heat sources and humidity. Two methods of feature extraction were proposed; spectrum band integration features, and the coefficients of polynomial function apmeasured spectra was. For classification a SVM, LDA and KNN were used. In another study [12], the problem of complex non-uniform plank background was addressed by image binarization and local thresholding, with a segmentation accuracy of 92%. It also shows a comparison between some known local thresholding methods.

Recently, deep neural networks have revolutionized computer vision. A fully convolutional neural network was proposed in [5] that reportedly achieved an overall accuracy rate of 99.14%. They used some basic data augmentation, i.e. rotation, hue, saturation,..., and polar transformation to obtain different defect shapes. The problem of overfitting was also addressed with L2 regularization of the objective function and dropout regularization of the network. A pair of inception convolutional modules were used to capture features from multiple scales. This study was followed up with a similar 16-layer deep convolutional neural network with a softmax output layer [6]. It achieved a 99.13% overall accuracy rate for three main categories of defects. The model was trained with the method of stochastic gradient descent with momentum (SGD-M). The authors emphasized the need for an automatic wood feature learning method, in contrast with complex extractions of features.

A study [16] points out, that the main drawback of deep learning methods is the need for a large amount of data, which is expensive to acquire and must be labelled with the ground truth by an expert. To circumvent this problem, the authors present a pixel-wise defect segmentation and classification method based on the Transfer learning of the Decaf CNN. Interestingly, a multinomial logistic regression (MLR) classifier is used to generate a heatmap, that is then thresholded with Otsu's method and segmented with Felzenszwalb's method. This study classifies 18 categories of wood defects with a high accuracy rate, but does not provide with an overall accuracy figure, since some of the defect categories are unique to this study. Similarly, in [20], a faster region-based convolutional network (faster R-CNN) achieved an accuracy rate of 96.1% for all defects combined. A Transfer learning method was used for the initial training, based on the pretrained neural network models: AlexNet, VGG-16, ResNet and GoogleLeNet. In this case the ResNet structure performed best, with a learning transfer accuracy of 80.6% for 4 classes of defects, but was the slowest. This regional matching method with regions of interest (RoI) addressed the problem of slow sliding window calculation for large pictures. The output layer of this structure is divided into a softmax classifier layer, and a positioning layer with rectangular shape limits. Transfer learning based on ResNet was also done in [8], with a transfer accuracy of 83.95% and a defect overall accuracy rate of 93.03%. The wood texture was also classified with a different dataset, achieving an accuracy of 94.41%. For comparison, a histogram of oriented gradient (HOG) and GLCM were used for feature extraction and an SVM classifier. Transfer learning consistently outperformed training from scratch, in all examples.

A notable defect detection method for various materials, based on the random-forest approach with variance of variance (VOV) profiles was proposed in [10]. VOV uses a sliding window and calculates the variance of each row and column in the window. Then the variance of these column and row variances are calculated, which can be used to describe the texture of the image and to amplify a small change in intensity. This method allowed for good defect detection performance with different backgrounds, with an average defect detection rate of 92.7%.

3. Methods

4. Experiments

5. Results

6. Discussion(optional)

7. Conclusion

8. References

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