Effect of Wood Surface Finish on Wood Species Classification Using Spectral Reflectance

Cheng-Kun Wang,[a] Peng Zhao,[b,]* and Jia-Le Yang [a]

Wood species can be classified by spectral reflectance. It is unclear whether finish coated on the wood surface affects the accuracy of wood species classification. This paper focused on this issue, using the spectral reflectance of 8 different kinds of finish for wood species classification. The spectral reflectance of wood surface coated with finish was modified by the transfer model in order to reduce the effect of finish on classification accuracy. The experimental results show that it is not feasible to use the spectral reflectance of wood samples coated with finish directly to classify wood species; the best classification accuracy using the eight finishes was 30%. After correcting the spectrum of wood samples coated with finishes with the direct standardization (DS) transfer model, the classification accuracy of the near-infrared (NIR) spectrum was close to that of the original spectrum without finish. However, the visible/near-infrared (VIS/NIR) spectrum did not achieve a good classification effect after correction with the DS transfer model.

DOI: 10.15376/biores.19.2.3060-3077

Keywords: Wood species classification; Finish; Spectral reflectance; Transfer model

Contact information: a: School of Electronic and Information Engineering, Heilongjiang University of Science and Technology, Harbin 150010, China; b: School of Computer Science and Communication Engineering, Guangxi University of Science and Technology, Liuzhou 545006, China;
** Corresponding author: Zhao Peng; Email: bit_zhao@aliyun.com*

INTRODUCTION

There are many wood species around the world. At present, people can classify wood species through spectroscopy, images, sound, and chemical process. Among these classification schemes, the spectral analysis scheme has the advantages of fast speed, high accuracy, and non-destructive testing. For example, Park *et al*. (2021) classified three coniferous wood species by use of wood extract and its near-infrared spectrum. Ma *et al*. (2021) proposed a new classification for 15 wood species based on spatially resolved diffuse reflection (*i.e.*, wavelength range 600 to 1000 nm). A portable near-infrared spectral measurement system based on principal component analysis (PCA) and support vector machine (SVM) was designed. Tuncer *et al*. (2021) classified pine tree species by means of NIR spectroscopy and with the first-order derivative and smoothing processing. Ma *et al*. (2019) used hyper-spectral images of the near-infrared spectrum to classify 15 wood species quickly. Pace *et al*. (2019) used PCA and partial least squares discriminant function regression (PLS-DFR) to analyze the spectral characteristics of wood, classifying forest tree species in the Atlantic Ocean. Bolzon *et al*. (2016) investigated the relationship between cross-section images and spectra of five wood species as an example to study the spectral and anatomical characteristics of wood in the process of transformation from wood into charcoals. Sohn *et al*. (2021) investigated the feasibility of rapid nondestructive classification of six *Amaranthus* species by using hand-held spectrometers in the field in different geographical regions of Korea. Zulfa *et al*. (2020) collected the leaf spectral characteristics of 19 mangrove species and explored whether the spectral reflectance data could be used to identify mangrove species. They found that chlorophyll content greatly influenced the spectrum, and the authors combined chlorophyll content with spectral reflectance, thus providing a new method for mangrove species classification.

There are two main categories by which to classify wood species by spectral analysis. One category is to classify wood species by using spectral transmittance. This category mainly tests wood by solid pressing, grinding, or making it into liquid, and tests are needed in the laboratory when collecting spectra from the wood material. The other category is to use the spectral reflectance of the wood surface to classify wood species. This category relies on the difference in the spectral reflectance of different wood species. When the spectral reflectance of wood surface is used for classification, a practical problem not yet considered until now is that the surface of actual household wood furniture is most frequently coated with a layer of finish. There are many types of finishes, which are all aimed at extending the service life of wood and preventing wood from cracking, decaying, and deforming (Evans *et al*. 2009). If the spectral analysis scheme is used to classify wood species, then it is necessary to remove the disturbance from the finish on wood surface. If this layer of finish is removed by sandpaper or other tools, the structural characteristics of the original wood surface will be inevitably damaged, which is undesirable. On the other hand, if the spectrum of wood surface with finish is used for classification directly, then questions will arise regarding the accuracy of wood species classification.

In this work, the following three comparative studies were carried out to address the above-mentioned problem. First, 20 wood species were selected as the experimental dataset, and a SVM classifier was used to perform wood species classification with the VIS/NIR spectrum and NIR spectrum for wood samples without coating finish. Second, the SVM classifier was trained with the wood dataset without coating finish to classify the spectral reflectance of wood surface with eight kinds of different finish coated in order to analyze the influence of different kinds of finish on the classification accuracy. Third, a transfer model was used to correct the spectral distortion caused by the finish on the wood surface so as to make the wood spectral classification more robust and accurate.

EXPERIMENTAL

A total of 20 wood species was used as the research dataset, including broadleaved and coniferous wood species. The sample dataset contained some wood species with similar colors and textures, and also contained wood species within the same genus. The detailed information on these wood species is shown in Table 1.

Eight kinds of finish were used for the experiments, as shown in Table 2. Number 2 and number 3 were wood wax oil, which is formed by catalpa oil, linseed oil, perilla oil, pine oil, palm wax, and a mixture of plant resin and pigment. Different wood wax oil products have different ingredients, so that two different manufacturer products of wood wax oil were considered. The finishes number 1~number 7 are clear, whereas number 8 is opaque. The wood surface coated with finish number 8 is reddish-brown.

Two spectrometers, the Ocean Optics USB2000+ and the FLAME-NIR spectrometer, were used in this paper to measure the diffuse reflectance. The effective wavelength ranges of the two spectrometers are 350 to 1000 nm and 950 to 1650 nm, respectively. The wavelength resolutions of the two spectrometers are 0.3 nm and 5.9 nm, respectively. These two wavelengths range just cover the visible band and part of the NIR band, and their total spectral coverage interval is 350 to 1650 nm.

Table 1. Information of Experimental Samples

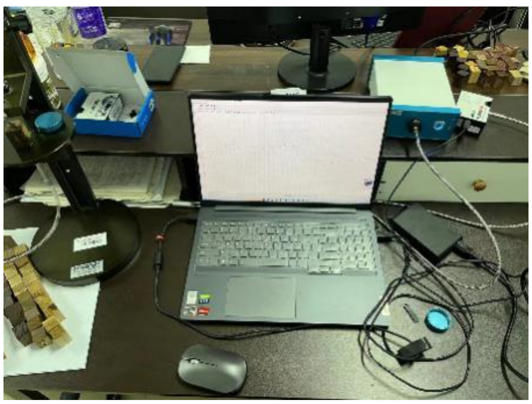
No.	Latin	Order	Family	Genus
1	*Acer pictum*	Sapindales	Aceraceae Juss.	*Acer*
2	*Albizia kalkora*	Fabales Bromhead	Mimosaceae	*Albizia*
3	*Amygdalus davidiana*	Rosales Bercht	Rosaceae	*Amygdalus*
4	*Betula platyphylla*	Fagales	Betulaceae Gray	*Betula*
5	*Cylicodiscus gabunensis*	Fabales Bromhead	Mimosaceae	*Cylicodiscus*
6	*Fraxinus chinensis*	Contortae	Oleaceae	*Fraxinus*
7	*Guibourtia demeusei*	Fabales Bromhead	Caesalpiniaceae	*Guibourtia*
8	*Intsia bijuga*	Fabales Bromhead	Caesalpiniaceae	*Intsia*
9	*Juglans mandshurica*	Juglandales	Juglandaceae	*Juglans*
10	*Magnolia fordiana*	Magnoliales	Magnoliaceae	*Magnolia*
11	*Millettia laurentii*	Fabales Bromhead	Papilionaceae	*Millettia*
12	*Phellodendron amurense*	Rutales	Rutaceae	*Phellodendron*
13	*Populus cathayana*	Salicales	Salicaceae	*Populus*
14	*Prunus avium*	Rosales Bercht	Rosaceae	*Prunus*
15	*Pterocarpus antunesii*	Fabales Bromhead	Papilionaceae	*Pterocarpus*
16	*Pterocarpus tinctorius*	Fabales Bromhead	Papilionaceae	*Pterocarpus*
17	*Quercus mongolica*	Fagales	Fagaceae	*Quercus*
18	*Shorea contorta*	Parietales	Dipterocarpaceae	*Shorea*
19	*Shorea laevis*	Parietales	Dipterocarpaceae	*Shorea*
20	*Tectona grandis*	Tubiflorae	Verbenaceae	*Tectona*

Table 2. Details of Finishes Used in the Experiment

No.	Name	Chemical composition
1	Tung oil	Fatty acid triglyceride
2	Wood wax oil I	Mixing of various natural oils
3	Wood wax oil II	Mixing of various natural oils
4	Polyester finish	Polyester resin
5	Polyurethane finish	Crylic acid
6	Nitrolacquer finish	Nitrocotton
7	Amino finish	Amino resin
8	water wood finish (brown)	Water soluble resin

To use the spectrometer to collect spectral data, the wood sample processing is required. First, a total of 25 wood blocks from different trees at different positions were selected for each wood species, and the shapes and sizes of these wood blocks were all different. To facilitate the collection of spectral data, these wood blocks were all cut into wood samples with size of 2 × 2 × 3 cm. The 2 × 2 cm section was the cross section, and the 2 × 3 cm section was either the radial section or the tangential section. Second, 4 wood samples of each wood block were randomly selected to get 100 wood samples with size of 2 × 2 × 3 cm. Due to the uneven burrs in the process of cutting wood and to get better spectral information, it is necessary to use sandpaper (800 to 1200 mesh) to polish the cross-section of a wood sample. Third, 40 samples were randomly selected from each wood species for testing set, and the remained 60 samples were used as the training set. The wood testing sets were divided into 8 groups, and each group was coated with the finish shown in Table 2. When a finish was brushed on wood surface which had been polished by sandpaper in advance, it was necessary to brush for the second time in 48 h after the first brush, and ensure that the wood surface is completely dry when collecting the spectra. Finally, the wood VIS/NIR spectrum may be sensitive to the influence of external factors (*e.g.*, temperature and humidity), so that the experimental environment was in a room with the stable temperature at 24 °C and humidity at 35%.

Figure 1(a) shows the basic framework of the entire spectral platform. The spectral platform in this experiment mainly includes a computer, spectrometer, optical fiber, and light source. Figure 1(b) shows wood samples coated with different finishes (*i.e.*, film formers). The samples on the top were coated with 8 different finishes, and samples on the bottom were coated with tung oil (*i.e.*, No. 1 in Table 2). Data acquisition was performed as follows. A basic calibration was performed using a standard whiteboard, then the wood sample is placed on the holder and the distance between the wood cross section and the fiber probe was adjusted. Finally, the spectral reflectance dataset was saved to the computer.



a

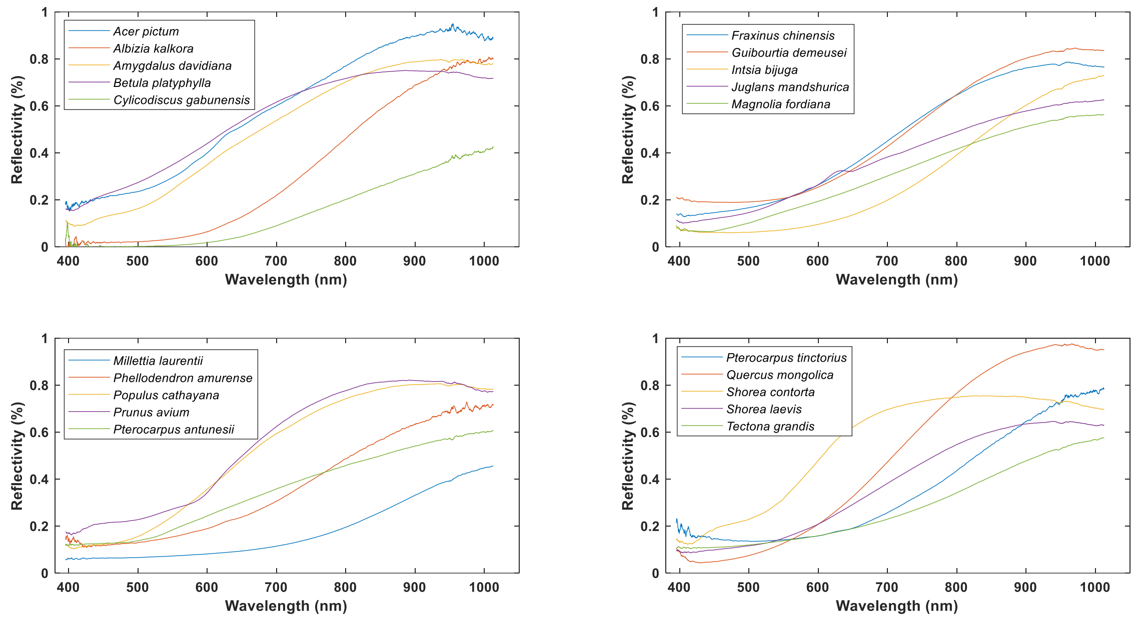
b

Fig. 1. Experimental platform and sample; a. spectral collection setup; b. samples coated with 8 finishes

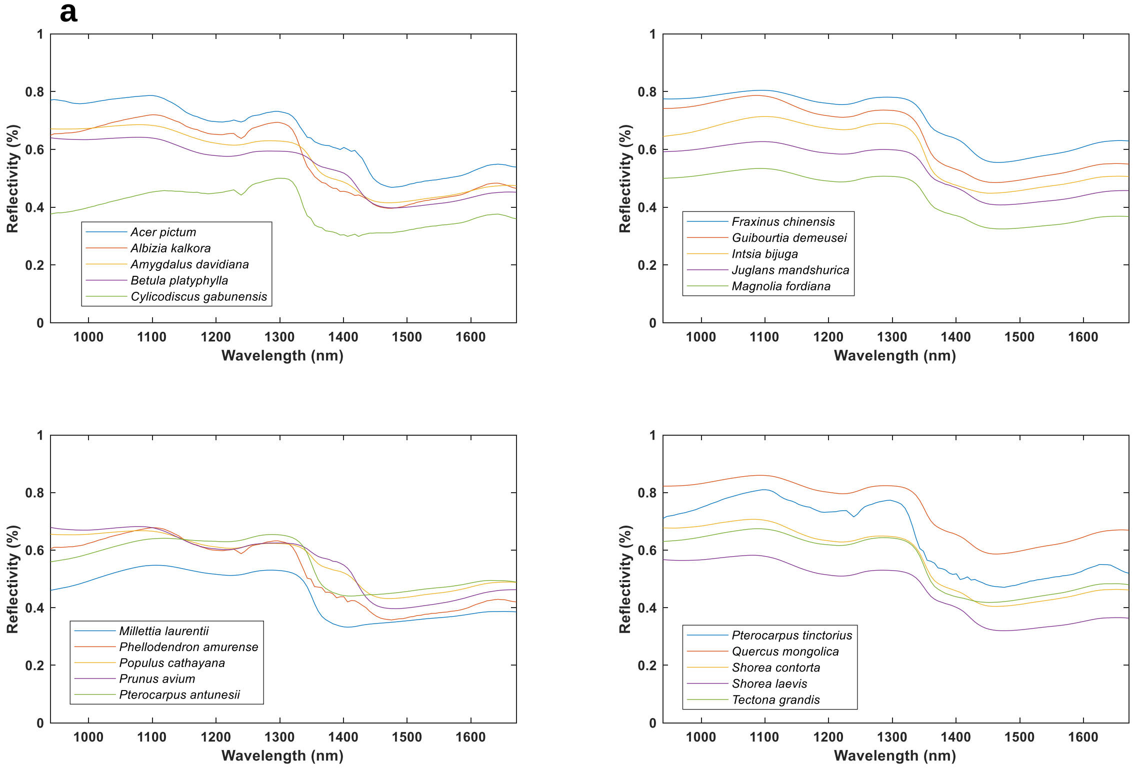
Spectral Pre-processing

The collected spectra cannot be directly used for classification. Due to the problem of the spectrometer itself, the visible spectrum fluctuates greatly in the range of both ends so that the spectra of 339.8 to 395.7 nm and 1012.7 to 1026.3 nm should be deleted. Figure 2 shows the spectral reflectance curves of the 20 wood species. Figure 2(a) corresponds to the spectral curve collected by the USB2000+ spectrometer, whereas Figure 2(b) the spectral curve collected by the FLAME-NIR spectrometer. In addition, standard normal variation (SNV) correction and smoothing correction with a moving window of 5 × 5 size should be used for the collected spectra to ensure that the spectral reflectance curve has a good recognition effect.

After the above-mentioned spectral curve correction, spectral dimension reduction should be performed. The original VIS/NIR spectral dimension is 1850D, whereas NIR is 128D. Therefore, it is necessary to reduce the redundant information and computational complexity. Different dimension reduction methods were used to compare the wood classification accuracy. These methods consisted of PCA (Reddy *et al*. 2020), multidimensional scaling (MDS) (Mignotte 2011), locally linear embedding (LLE) (Yu *et al*. 2020), Laplacian (Belkin and Niyogi 2003), and Kernel PCA (Alhayani and Ilhan 2017). The used classifier was an SVM classifier (Byvatov and Schneider 2003).



a



b

Fig. 2. Spectral reflectance of a cross section of wood species; a. VIS/NIR spectra; b. NIR spectra

Effects of Different Finishes on the Spectral Reflectance Curve of Wood Surface

The main purpose of coating finish on wood surface is to prevent decay, deformation, and cracking of wood material. There are great differences in the composition of different finishes. For wood, there is pure natural tung oil, wood wax oil, amino, polyurethane, and other finishes based on chemical composition. In Figure 3, the spectral reflectance curve of *Pterocarpus tinctorius* wood species by use of different finishes is given, and the labeling is the same as that of Table 2.

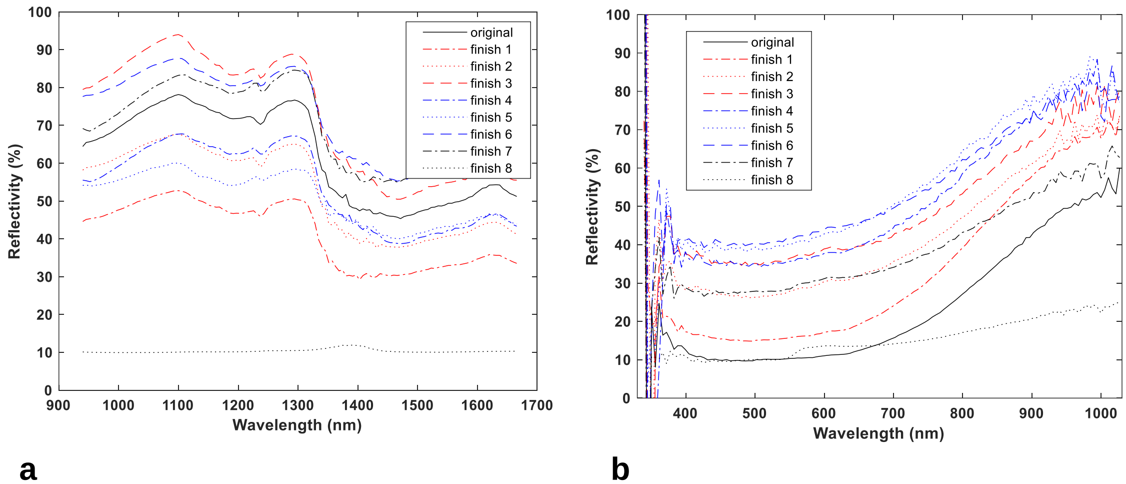


Fig. 3. Spectral reflectance of *Pterocarpus tinctorius* with different film formers; a. NIR spectral curve; b. VIS/NIR spectral curve

In Fig. 3 (a), the NIR spectral curve exhibited some translations when the sample was coated with each of the eight finishes. Specifically, if the finish has a large reflection, the whole spectrum will move up; if the finish has a large absorption, the whole spectrum will move down. However, the spectrum of finish 8 (water wood finish (brown)) was different from that of other finishes, since its spectral reflectance value was small. Figure 3 (b) illustrates the wood spectral reflectance curves produced by different finishes in the VIS/NIR band. The spectral curve with respect to finish 1 (tung oil) was close to the original spectral curve without finishes, but the spectral curve with respect to finish 8 still had small spectral values. In this paper, only diffuse reflectance was considered, and the specular reflectance will be investigated in our future work. The wood surface is brushed two times with a finish, and the finish thickness is approximately 0.2 to 0.3 mm.

In this part, the spectra of wood samples without any finish were taken as the training dataset, and the classifier was trained to get the SVM. Then, the wood spectral classification was directly used to the testing dataset coated with different finishes to obtain the specific classification accuracy. The goal of this part was to evaluate whether the wood spectral curve coated with different finishes can be directly classified by use of the SVM classifier trained with the original spectra without any finish.

Wood Species Classification using Corrected Spectral Curve of Wood Surface Coated with Finishes Based on Transfer Model

The main purpose of a transfer model is to realize model sharing to reduce the difficulty of model reconstruction. By using the transfer model, the problem that the spectra of wood surface with and without finishes collected by the same spectrometer are different can be solved. The transfer models of different finishes are established to repair the spectral changes of the wood surface caused by coating finishes. The specific procedure is shown in Fig. 4.

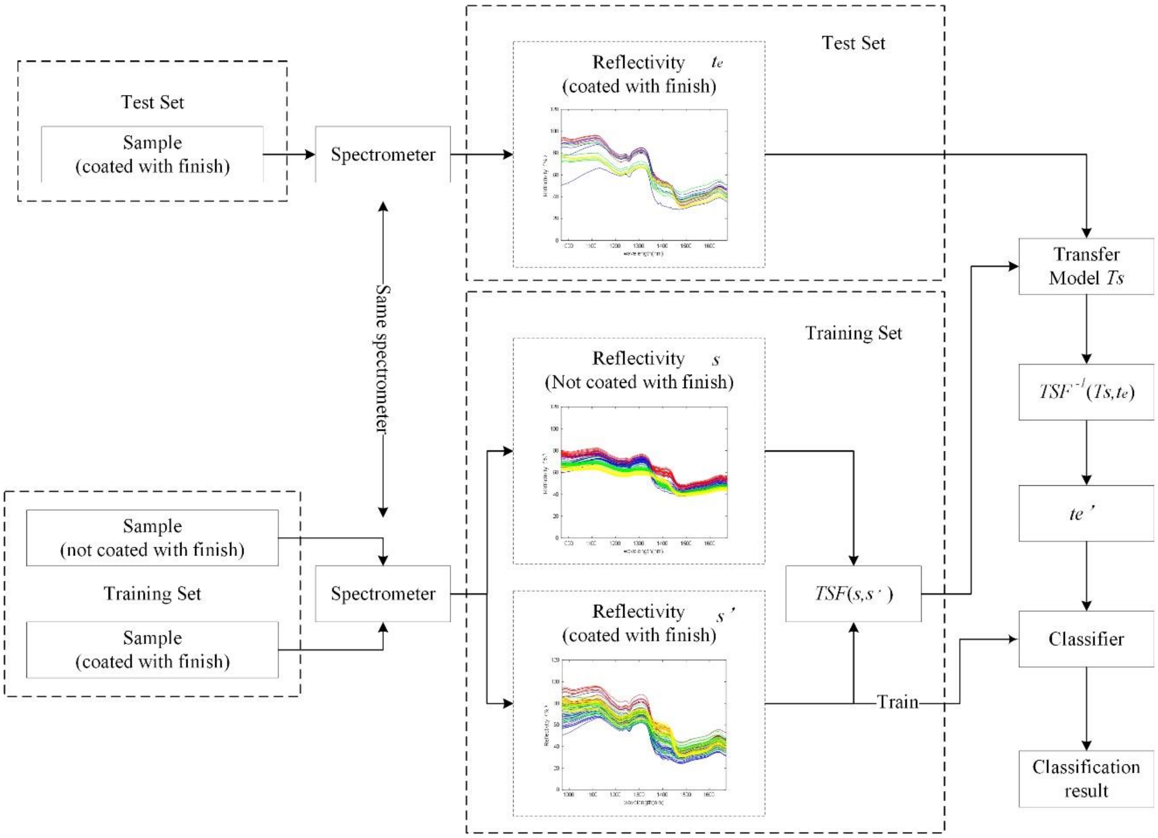


Fig. 4. Flow of spectrum correction using transfer model

As shown in Fig. 4, first, the original spectral reflectance curve of wood cross section without finishes and the corresponding curve with coated finish were collected and denoted as s, s' respectively. Then, the transfer model was generated and saved by s and s', and this transfer model was denoted as T_s. Its relationship with s and s' is expressed by Eq. 1. It is not difficult to find that each kind of finish has a transfer model generated by the spectrum of the training set.

$$T_s = TSF(s, s') \tag{1}$$

Next, the classifier SVM was trained and obtained through the original spectral reflectance curve of the training set without finishes. Finally, when encountering wood sample coated with finish, the transfer model can be used for correction. Assuming that an unknown sample coated with finish is denoted as t_e, the correction can be carried out in Eq. 2, and the corrected spectra can be sent to the SVM classifier for classification. Here TSF^{-1} in Eq. 2 represents the process of correcting with transfer model T_s, and the correction result is denoted as $t_e{}'$.

$$t_e{}' = TSF^{-1}(T_s, t_e) \tag{2}$$

Currently, the commonly used transfer models include direct standardization (DS) and piecewise direct standardization (PDS) (Tan and Brown 2001). In this paper, the DS algorithm was used to correct the wood spectrum with coating finish. The main idea of this algorithm is to establish the mapping relationship between the original spectrum and the spectrum with coating finish.

Let the original spectrum of wood species collected by the spectrometer be X_o, and the corresponding spectrum with finish be X_f. The dimensions of X_o and X_f are both $n \times m$; where n represents the number of samples, whereas m represents the spectral dimension. The relationship between X_o, X_f, and transformation matrix F can be established by using Eq. 3. The transformation matrix F can be solved in Eq. 4.

$$X_o = X_f F \tag{3}$$

$$F = X_f^+ X_o \tag{4}$$

Since the number of samples n and spectral dimension m are not necessarily equal, it is not feasible to directly solve the inverse matrix of X_f. Therefore, the X_f^+ in Equation (4) represents the generalized inverse matrix of X_f. This matrix can be solved by Moore-Penrose's solution for generalized inverse matrix (Barata and Hussein 2012). The specific solution is shown in Eq. 5, where $inv(A)$ represents solving the inverse matrix of square matrix A, and the size of the generalized inverse matrix generated is $m \times m$.

$$X_f^+ = inv\left(X_f' X_f\right) X_f' \tag{5}$$

Assuming that the spectral reflectance matrix corresponding to the unknown wood sample coated with one finish is X_T, the F matrix can be used to correct the X_T through Equation (6), and the corrected X_T^c can be obtained.

$$X_T^c = X_T F \tag{6}$$

Through the above-mentioned procedure, the transfer models of 8 kinds of finish can be established, respectively. The spectral curve of wood sample coated with one kind of finish can be corrected by using this transfer model so as to improve the classification accuracy.

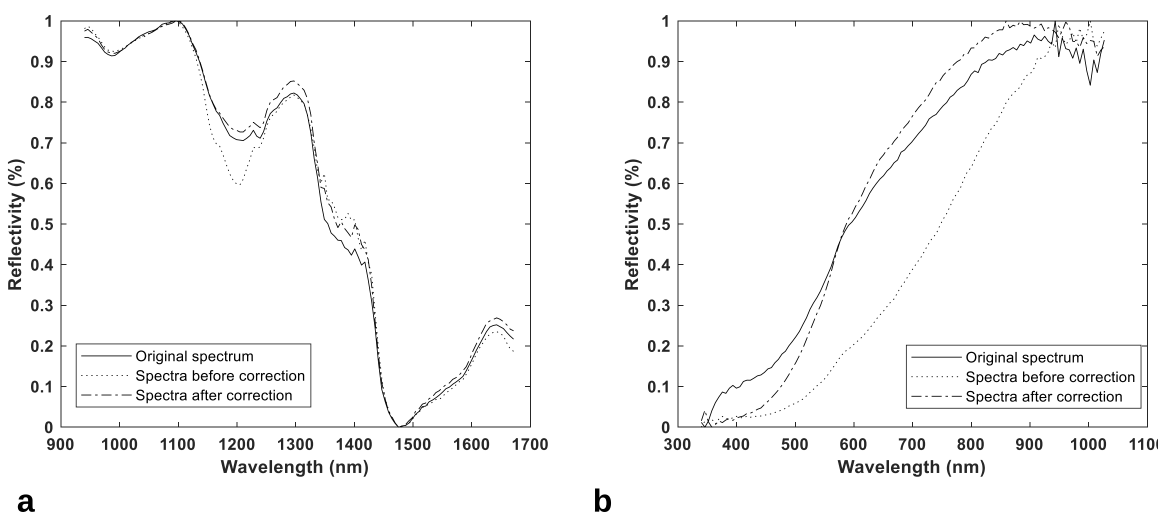


Fig. 5. Spectral reflectance before and after correction; a. NIR band; b. VIS/NIR band

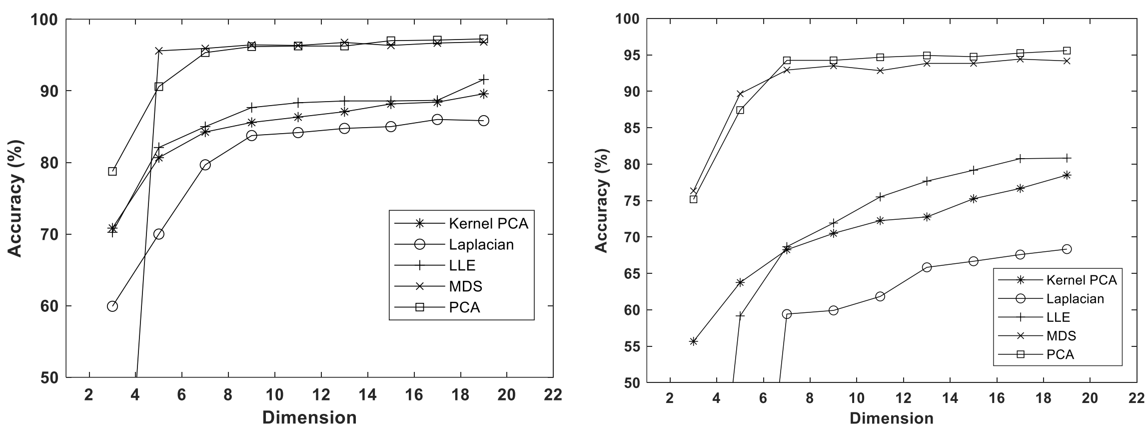
Figure 5 shows the original spectrum of *Acer pictum* wood species, the spectrum with finish without DS correction, and the spectrum with finish after DS correction. Figure 5(a) corresponds to the NIR spectral curve, whereas Fig. 5(b) VIS/NIR spectral curve. It can be seen that the spectral curve with finish without DS correction exhibited a large difference from the original spectral curve. However, the difference between the spectral curve with finish after DS correction and the original spectral curve was significantly reduced.

RESULTS AND DISCUSSION

Wood Species Classification Using Original Spectral Curve

In this section, the influence of wood surface finishes on classification accuracy will not be considered, and the original spectrum without coating any finish on wood surface will be used. Five different dimension reduction methods and the SVM classifier were used to classify wood species. The K-folding method in cross-validation was used here (Refaeilzadeh *et al*. 2009) with $K = 8$, which is determined using the grid search. All program design and data analysis were implemented in MATLAB 2019B in this paper.

Figure 6(a) shows the classification accuracy of the original spectral classification collected by the FLAME-NIR spectrometer. It can be seen that the MDS and PCA methods achieved good classification effect, while the other three-dimension reduction methods were not particularly good. The classification accuracy leveled off approximately when the spectral dimension was larger than 8. Figure 6(b) shows the original spectral classification accuracy collected by the USB2000+ spectrometer. It can be seen that MDS and PCA methods still achieved better classification effects. Moreover, Fig. 6 shows that the classification accuracy of NIR spectra collected by FLAME-NIR spectrometer was higher than that of VIS/NIR spectra collected by USB2000+ spectrometer. The reason is that the visible spectral band is often influenced by the radian illumination, wood sample's water content, and its cutting procedure.



a b

Fig. 6. Classification accuracy of the original spectrum; a. NIR band; b. VIS/NIR band

Table 3. Best Dimensions and Highest Classification Accuracy

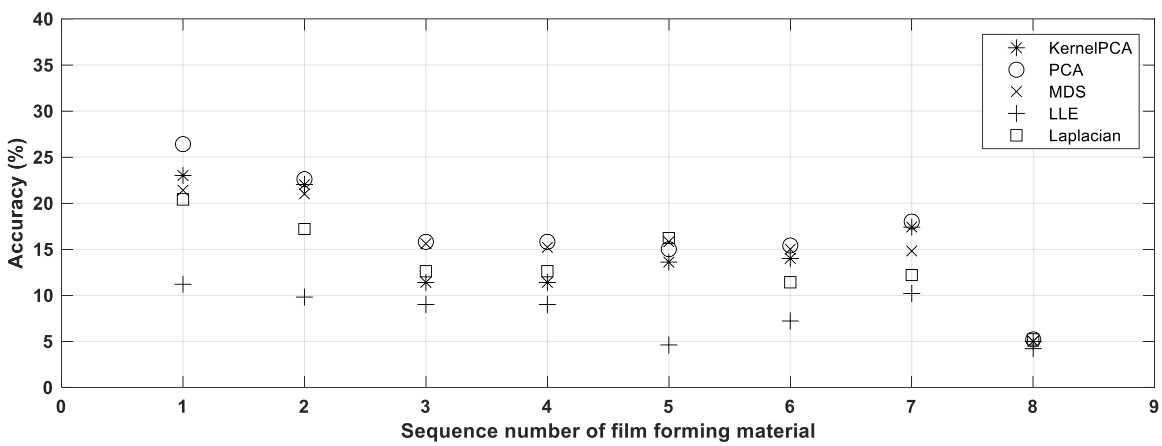
Spectrograph	Flame (NIR-950 to 1650 nm)		USB2000+(VIS/NIR-350 to 1000 nm)	
Method	Dimensionality	Accuracy (%)	Dimensionality	Accuracy (%)
Kernel-PCA	19	89.58%	19	78.50%
Laplacian	17	86.00%	19	68.33%
LLE	19	91.58%	19	80.83%

MDS	19	96.83%	17	94.42%
PCA	19	97.25%	19	95.58%
Original	-	97.83%	-	96.33%

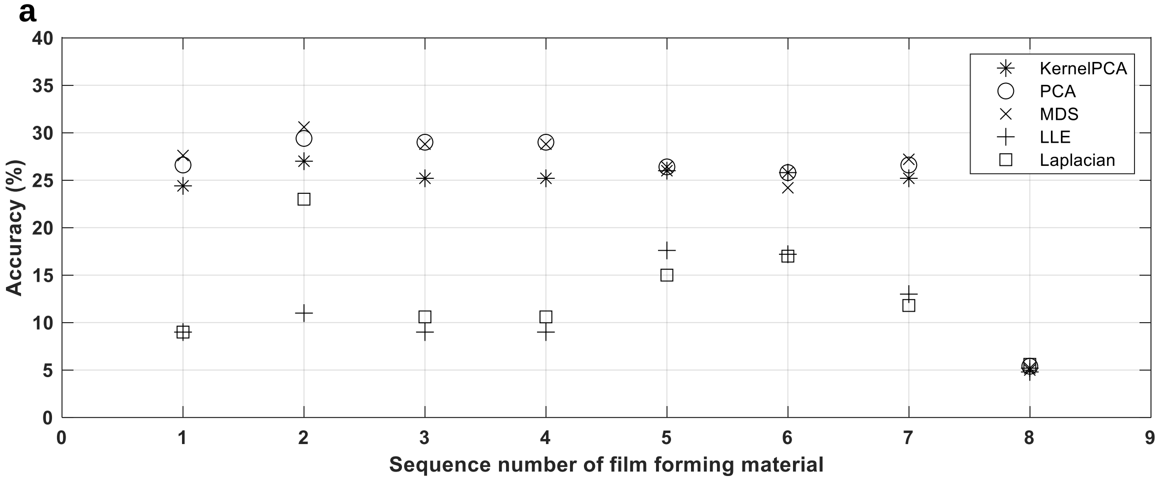
The highest classification accuracy of spectral curves collected by two spectrometers in view of different spectral dimension reduction methods is given in Table 3. The classification accuracy without any dimension reduction is also shown in Table 3 for comparison. If spectral dimension reduction was not carried out, the classification accuracy was the best. However, such an approach takes a lot of computing time, so it is necessary to carry out the dimension reduction.

Influence of Wood Surface Finishes on Spectral Classification Accuracy

This section covers the spectral classification accuracy of wood surfaces coated with finishes by SVM classifier trained with the original spectral dataset without coating finishes. In Fig. 7(a), the classification accuracy of VIS/NIR（350~1000 nm）spectra is given, whereas in Fig. 7(b), that of NIR（950~1650 nm）spectra is given. For the 5 spectral dimension reduction methods, the optimal spectral dimension is used, as in Table 3.



a



b

Fig. 7. Classification results of spectral reflectance of different film forming substances; a. VIS/NIR band; b. NIR band

Neither VIS/NIR spectra nor NIR spectra was able to be used to classify wood species when coated with finishes. Figure 7 shows that the highest classification accuracy was less than 32%. The classification accuracy of the finish 8 was close to 5%. The main reason is that the similarity between the spectrum of finish 8 and that of wood surface is too low. Table 4 shows the optimal dimension reduction method and its corresponding classification accuracy with 8 different finishes. It can be seen that the classification accuracy of finishes 1 to 7 was between 15% and 30%. The PCA and MDS dimension reduction methods achieved higher classification accuracy.

Table 4. Highest Accuracy and Dimensionality Reduction Method with Film Forming Material

	Film	1	2	3	4	5	6	7	8
VIS/NIR	Dimension method	PCA	PCA	PCA	MDS	MDS	PCA	PCA	PCA
	Accuracy (%)	26.4	22.6	15.8	15.8	15.8	15.4	18.0	5.2
NIR	Dimension method	MDS	MDS	PCA	PCA	MDS	PCA	MDS	LAP
	Accuracy (%)	27.6	30.6	29.0	29.0	26.4	25.8	27.2	5.6

The above analysis shows that directly using the SVM classifier trained with the original spectral dataset without coating finishes to classify wood spectral curves with finishes is not applicable. The transparent finishes achieved slightly higher classification accuracy, whereas the non-transparent finish could not be used for wood classification at all.

Next, to be considered is the classification accuracy of each wood species with different finishes. Figure 8 shows the specific classification accuracy of NIR spectra using PCA, where 20 wood species are represented from left to right and 7 finishes are represented from top to bottom. As the classification accuracy of finish 8 was too low, it is not included in Fig. 8. The last row represents the average classification accuracy.

As shown in Fig. 8, the classification accuracy of No. 5, 12, 16, 18 wood species was relatively high, and that of No.4, 11, 15, 19 wood species was relatively good. The remaining wood species were unrecognizable. Intuitively, these wood species can be divided into two categories: one category is with dark surface color, such as No.5, 16, 18, 11, 15, 19; the other is with light surface color and simple texture, such as No.12 and No.4. These wood species have a single surface color, and the spectral curve of wood surface changes little after coating the finish material, so that they can be classified using SVM classifier trained with the original spectral dataset without coating finishes.

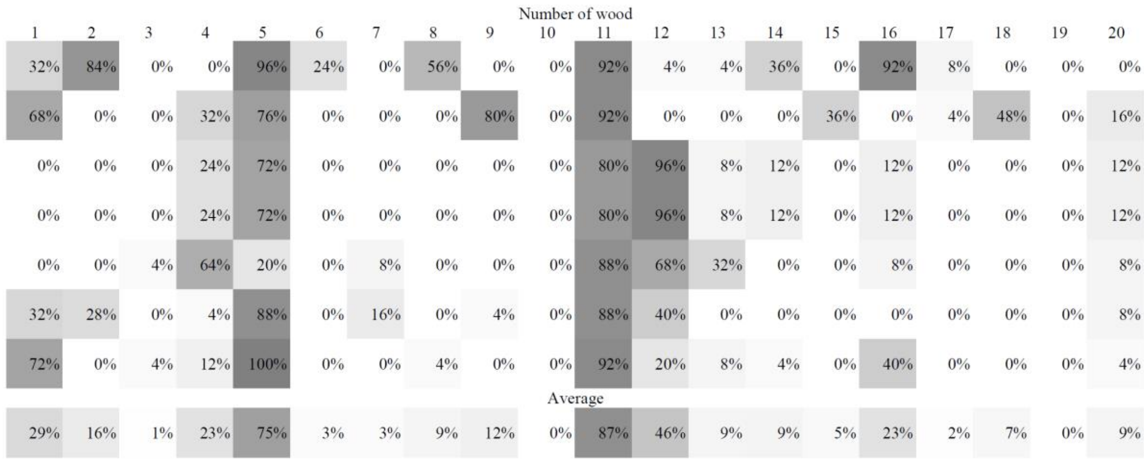


Fig. 8. Accuracy of each wood with VIS spectral reflectance under different finish

Figure 9 shows the specific classification accuracy of each wood species in the VIS/NIR band. In comparison with Fig. 8, the overall classification accuracy has declined. The classification accuracy of different finish varies greatly. In terms of wood species, wood species No. 5 and No. 11 have better classification results, since both species have dark surface color.

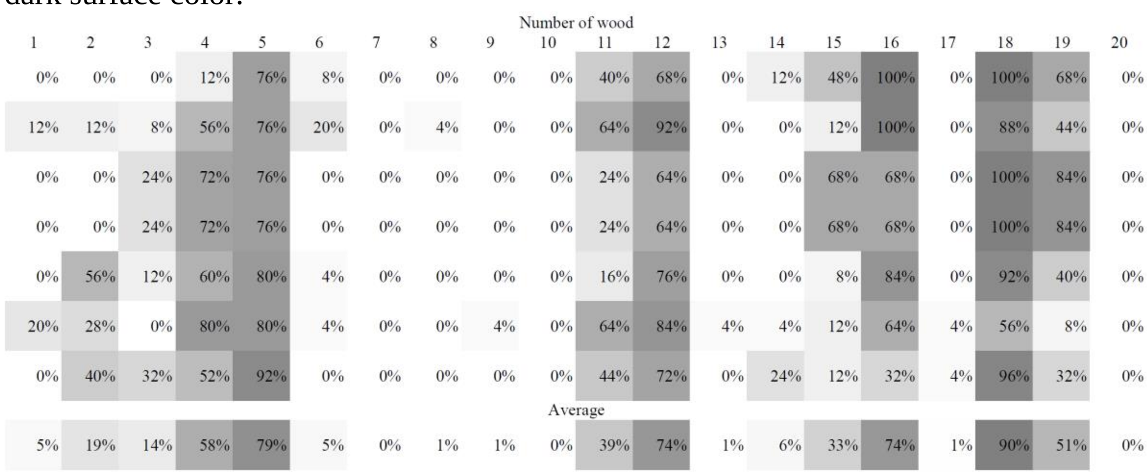


Fig. 9. Accuracy of each wood with VIS/NIR spectral reflectance under different finish

Wood Spectral Classification Correction using the DS Algorithm

This section discusses the spectral classification correction effect of coating finishes with transfer model correction. Figure 10 shows the classification accuracy of different finishes with the DS algorithm, and the used dimension reduction method is PCA. It can be seen that after using the DS algorithm to correct the spectral curve of wood surface coated with finishes, the correction effect of NIR band is better. The classification accuracy of finish 1, 2, and 3 exceeded 95%, and that of finishes 4 to 7 was between 80% and 91%. The classification accuracy of finish 8 was low (*i.e.*, 5%). In contrast, the correction effect of the DS algorithm on VIS/NIR band was not ideal. Except for the finish 1, its classification accuracy with other finishes was lower than 15%. In view of the feature dimension, when the feature dimension exceeded 7, the classification accuracy tended to be stable, which is consistent with the previous results.

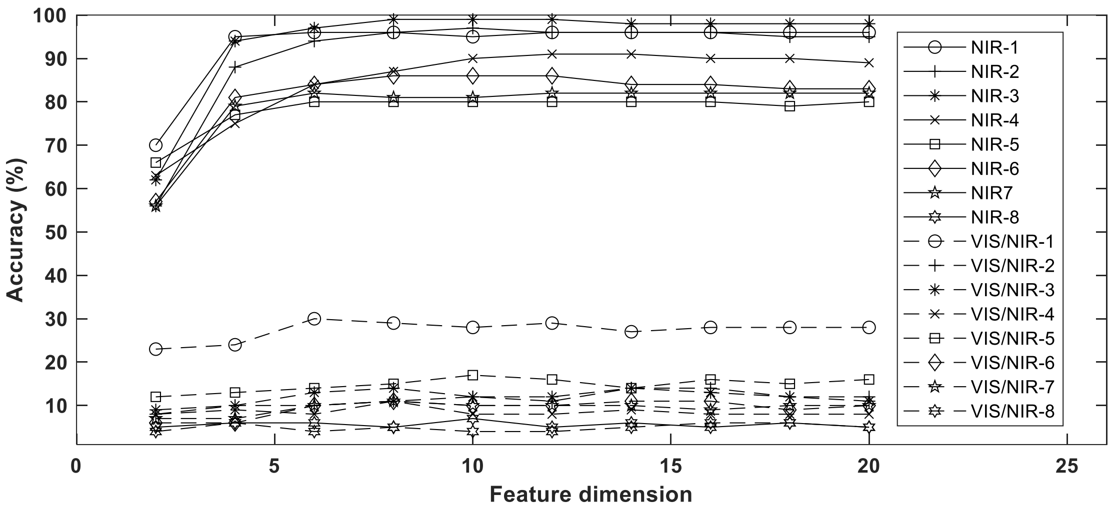


Fig. 10. Classification accuracy under DS correction algorithm

In terms of finishes, finishes 1 to 3 belong to natural transparent finishes, and the classification effect of NIR band corrected by the DS algorithm was good. Finishes 4 to 7 belong to artificially produced transparent finishes. The DS algorithm could be used to correct NIR band to some extent, but the correction effect was limited. Finish 8 is a non-transparent film-forming substance, so that it cannot reflect the characteristics of the original wood surface and it cannot be corrected. Table 5 shows the highest classification accuracy and the best feature dimension after correction using the DS algorithm.

Table 5. Optimal Feature Dimension and Accuracy after DS Algorithm Correction

	Film	1	2	3	4	5	6	7	8
VIS/NIR	Feature dimension	6	14	8	8	15	8	8	4
	Accuracy (%)	30%	14%	14%	11%	17%	11%	11%	6%
NIR	Feature dimension	6	10	8	12	6	8	6	10
	Accuracy (%)	96%	97%	99%	91%	80%	86%	82%	7%

Comparing Tables 4 and 5, the classification accuracy of VIS/NIR spectral curve of wood surface coated with finishes decreased to some extent, instead of rising after the DS algorithm was used for correction. This phenomenon may arise from the following reasons. First, the VIS/NIR spectrum is sensitive to the wood surface color, and the wood surface color will usually change when coated with finishes. For example, finish 1 (Tung oil) itself has a yellow color, and the wood surface will become yellow after coating this finish material. Second, the VIS/NIR spectral curve of wood species is usually smooth, and even the spectral reflectance difference of wood samples with similar colors or textures without coating finishes is not obvious. After correction by the DS algorithm, the spectral curve of these wood samples may not be recognized by the classifier SVM.

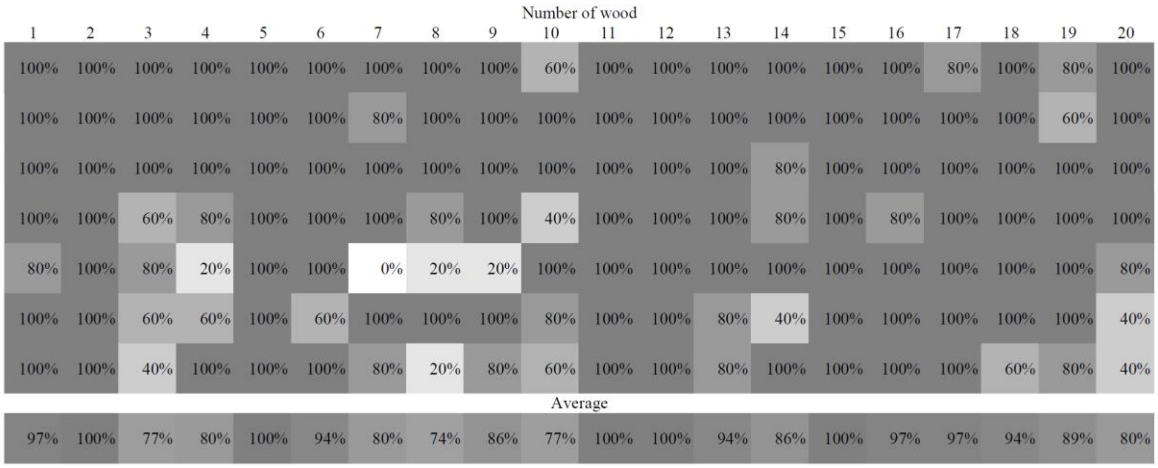


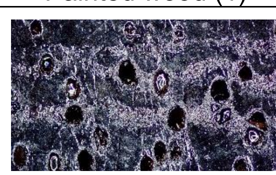
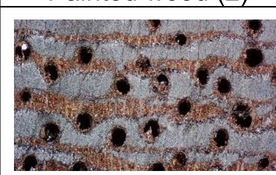
Fig. 11. Accuracy of each type of wood after correction with DS

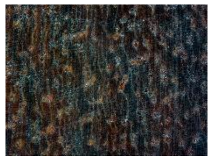
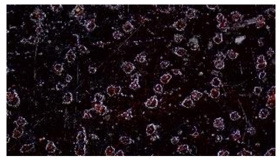
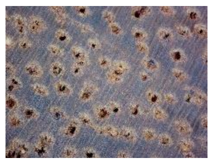
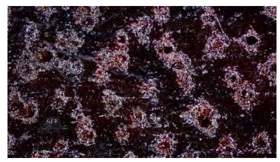
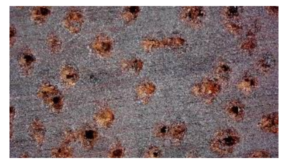
Figure 11 shows the specific classification accuracy of each wood species after correction by the DS algorithm. PCA was used in the dimension reduction, and the spectral dimension corresponds to the best feature dimension in Table 5. The classification accuracy after DS correction was significantly better than that before correction, and the average accuracy of most wood species was higher than 80%. The classification accuracy of wood species No. 3, 8, 10 was lower than 80%. The reason is that the surface texture and color of these three species were very different. Due to the limited number of training samples in the training dataset, the classification accuracy was low. Through the above analysis, it can be found that the NIR spectra coated with finishes can be corrected by using the DS transfer model, and the corrected spectra can be directly classified by the classifier SVM trained by the original spectra. However, this method does not apply to VIS/NIR spectra coated with finishes.

Wood Species Classification using Image Textural Features

Next, wood species classification was based on image textural features. To classify wood samples with coated finishes, an imaging classification scheme may be used, whereas a sound or chemical process classification scheme may not be used. For example, Table 6 illustrates the cross sections of wood samples of 5 wood species without finishes and with finishes “Wood wax oil I” (Painted wood (1)) and “Tung oil” (Painted wood (2)). It can be seen that there were obvious differences for samples with and without finishes with respect to colors and textures. The computed textural features gray level co-occurrence matrix (GLCM) and local binary pattern (LBP) of wood species No. 1 and No. 2 in Table 6 with and without finishes are illustrated in Fig. 12, which indicates the above-mentioned differences in terms of textures for the same wood species.

Table 6. Cross Sections of 5 Wood Species Without and With Two Finishes

Num	Latin	Raw wood	Painted wood (1)	Painted wood (2)
1	*Millettia laurentii*			

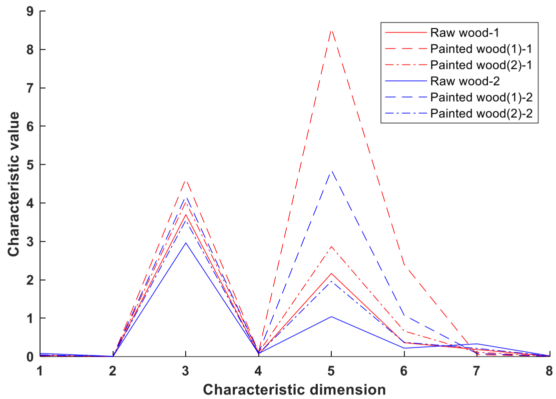
2	*Albizia kalkora*			
3	*Acer pictum*			
4	*Pterocarpus tinctorius*			
5	*Intsia bijuga*			

The wood species classification was also performed by use of GLCM and LBP textural features and SVM classifier trained with original samples without finishes for the 20 wood species in Table 1. The experimental configuration is as follows. For each wood species, there were 50 training samples and 15 testing samples, respectively. The random selection was used to divide each training set and testing set. The grid search is used to obtain the optimal SVM parameters. The classification accuracy is illustrated in Table 7, which indicates that it was impossible to classify wood species samples with coated finishes by use of imaging features. Some image processing techniques such as image filtering, image segmentation, and feature extraction improved the classification scheme, but the classification accuracy was still not satisfied. Therefore, this imaging classification scheme was not used in the end.

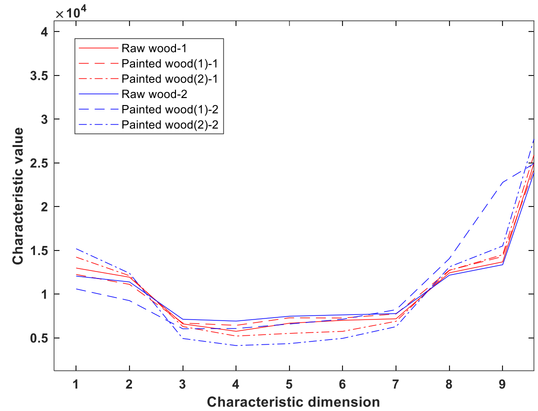
In our opinion, many previous studies in terms of wood vessel features have been based on imaging classification schemes. Therefore, in this Section, a comparison experiment was performed, but the classification accuracy was poor. As can be seen in Table 6, wood tissue features such as pores or parenchyma change greatly due to the filling finish, which makes it hard to carry out classification by use of image processing approaches. Therefore, the spectral analysis approach was used for wood species classification with coated finishes.

Table 7. Classification Accuracy for 20 Wood Species with 2 Finishes by Use of Textural Features

Texture	Tung Oil	Wood Wax Oil I
GLCM	12.00%	10.67%
LBP	13.30%	12.67%



a



b

Fig. 12. The textural features of 2 wood species in Table 6 of raw wood and painted wood; a. GLCM feature; b. LBP feature.
(Wood-1 refers to wood species No.1 in Table 6, and Wood-2 refers to wood species No.2 in Table 6；Painted wood (1) and Painted wood (2) refer to wood painted with “Wood wax oil I” and “Tung oil”, respectively)

CONCLUSIONS

1. The spectral curve of wood surfaces coated with finishes will change to some extent, which will affect the wood species classification accuracy. Specifically, the influence of different finish on visible/near-infrared (VIS/NIR) spectra was found to be higher than that on NIR spectra. If finish is non-transparent, its spectral reflectance cannot reflect the characteristics of the original wood sample.
2. Wood species classification can be performed using the original spectral curves, but the support vector machine (SVM) classifier trained with the original spectra cannot be used for wood samples coated with finishes.
3. The direct standardization (DS) transfer model can be used to correct the NIR spectra of wood samples coated with finishes and achieve much better classification accuracy, but the VIS/NIR spectra coated with finishes cannot be corrected effectively.
4. If the finish substance is transparent, then the DS correction algorithm can be used to correct the NIR spectra of wood samples, and the corrected spectra can be directly classified using the SVM classifier trained by the original wood spectra without finishes.
5. With respect to chemical effects, the transformations of wood spectral curves are caused by some chemical substances such as extractives from knots penetrating through the finish layer (Coniglio *et al*. 2023; Guessan *et al*. 2023). These extractives are usually stilbenes, lignans and flavonoids in wood samples with knots of pine. The specific chemical effects of these extractives are not discussed in detail here, as this article concentrates on wood species classification with physical and intelligent algorithms.

ACKNOWLEDGEMENTS

This research was supported by the Basic Research Expenses of Provincial Institutions of Higher Learning in Heilongjiang Province (Grant number 0000090336), the National Natural Science Foundation of China (Grant number 62265001), and the Guangxi University of Science and Technology Doctoral Research Fund (Grant number 22Z07).

Availability of Data and Materials

The wood spectral dataset used in this work is confidential, but this dataset used to support the findings of this study is available from the corresponding author upon request after this article is accepted and published online.

Competing Interests

The authors declare that they have no competing interests.

Author Contributions

Peng Zhao proposed the research idea and the experimental framework, writing the whole manuscript. Chengkun Wang carried out the wood species recognition experiments and collated the experimental results. Jiale Yang collated the experimental results. All authors read and approved the final manuscript.

REFERENCES CITED

Alhayani, B., and Ilhan, H. (2017). "Hyper-spectral image classification using dimensionality reduction techniques," *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering* 5(4), 71-74. DOI: 10.17148/IJIREEICE.2017.5414

Barata, J. C. A., and Hussein, M. S. (2012). "The Moore–Penrose pseudo inverse: A tutorial review of the theory," *Brazilian Journal of Physics* 42(1), 146-165. DOI: 10.1007/s13538-011-0052-z

Belkin, M., and Niyogi, P. (2003). "Laplacian eigenmaps for dimensionality reduction and data representation," *Neural Computation* 15(6), 1373-1396. DOI: 10.1162/089976603321780317

Bolzon de Muñiz, G. I., Carneiro, M. E., Ribeiro Batista, F. R., Schardosin, F. Z., and Nisgoski, S. (2016). "Wood and charcoal identification of five species from the miscellaneous group known in Brazil as "angelim" by near-IR and wood anatomy," *Maderas. Ciencia Y tecnología*, 18(3), 505-522. DOI: 10.4067/S0718-221X2016005000045

Byvatov, E., and Schneider, G. (2003). "Support vector machine applications in bioinformatics," *Applied Bioinformatics* 2(2), 67-77.

Coniglio, R., Gaschler, W., and Dieste, A. (2023). "Knot extractives responsible for the yellowing of white-coated pine wood," *European Journal of Wood and Wood Products*, 81(5), 1109-1117. DOI: 10.1007/s00107-023-01938-3

Evans, P. D., Wingate-Hill, R., and Cunningham, R. B. (2009). "Wax and oil emulsion additives: How effective are they at improving the performance of preservative-treated wood?" *Forest Products Journal* 59(1/2), 66-70. DOI:

10.3724/SP.J.1077.2011.00321

Guessan, J. L. L. N., Niamke, B. F., Yao, N. J. C., and Amusant, N. (2023). "Wood extractives: main families, functional properties, fields of application and interest of wood waste," *Forest Products Journal* 73(3), 194-208. DOI: 10.13073/FPJ-D-23-00015

Ma, T., Inagaki, T., Ban, M., and Tsuchikawa, S.. (2019). "Rapid identification of wood species by near-infrared spatially resolved spectroscopy (NIR-SRS) based on hyperspectral imaging (HSI)," *Holzforschung* 73(4), 323-330. DOI: 10.1515/hf-2018-0128

Ma, T., Inagaki, T., and Tsuchikawa, S. (2021). "Demonstration of the applicability of visible and near-infrared spatially resolved spectroscopy for rapid and nondestructive wood classification," *Holzforschung* 75(5),419-427. DOI: 10.1515/hf-2020-0074

Mignotte, M. (2011). "MDS-based multiresolution nonlinear dimensionality reduction model for color image segmentation," *IEEE Transactions on Neural Networks* 22(3), 447-460. DOI: 10.1109/TNN.2010.2101614

Pace, J. H. C., Figueiredo Latorraca, J. V., Hein, P. R. G., Carvalho, A. M. D., and Silva, C. E. S. D. (2019). "Wood species identification from Atlantic forest by near infrared spectroscopy," *Forest Systems* 28(3), 3-6. DOI: 10.5424/fs/2019283-14558

Park, S. Y., Kim, J. H., Kim, J. C., Yang, S. Y., and Choi, I. G. (2021). "Classification of softwoods using wood extract information and near infrared spectroscopy," *BioResources* 16(3), 75-80. DOI: 10.15376/biores.16.3.5301-5312

Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., Kaluri, R., Rajput, D. S., and Srivastava, G. (2020). "Analysis of dimensionality reduction techniques on big data," *IEEE Access* 8, 54776-54788. DOI: 10.1109/ACCESS.2020.2980942

Refaeilzadeh, P., Tang, L., and Liu, H. (2009). "Cross-validation," *Encyclopedia of Database Systems* 5, 532-538. DOI: 10.1007/978-0-387-39940-9_565

Sohn, S. I., Oh, Y. J., Pandian, S., Lee, Y. H., Zaukuu, J. L. Z., Kang, H. J., Ryu, T. H., Cho, W. S., Cho, Y. S., and Shin, E. K. (2021). "Identification of *Amaranthus* species using visible-near-infrared (VIS-NIR) spectroscopy and machine learning methods," *Remote Sensing* 13(20), 4149. DOI: 10.3390/rs13204149

Tan, H. W., and Brown, S. D. (2001). "Wavelet hybrid direct standardization of near-infrared multivariate calibrations," *Journal of Chemometrics* 15(8), 647-663. DOI: 10.1002/cem.660

Tuncer, F. D., Dogu, D., and Akdeniz, E. (2021). "Efficiency of preprocessing methods for discrimination of anatomically similar pine species by NIR spectroscopy," *Wood Material Science & Engineering* 1-10. DOI: 10.1080/17480272.2021.2012821

Yu, Z., Qin, L., Chen, Y., and Parmar, M. D. (2020). "Stock price forecasting based on LLE-BP neural network model," *Physica A: Statistical Mechanics and Its Applications* 553, 124197. DOI: 10.1016/j.physa.2020.124197

Zulfa, A. W., Norizah, K., Hamdan, O., Zulkifly, S., and Rhyma, P. P. (2020). "Discriminating trees species from the relationship between spectral reflectance and chlorophyll contents of mangrove forest in Malaysia," *Ecological Indicators* 111, article 106024. DOI: 10.1016/j.ecolind.2019.106024

Article submitted: December 31, 2023; Peer review completed: March 9, 2024; Revised version received and accepted: March 17, 2024; Published: March 27, 2024.
DOI: 10.15376/biores.19.2.3060-3077