

# NIR spectral imaging for the in-line detection of preservatives in recovered wood

Dirk Mauruschat, Jochen Aderhold, Burkhard Plinke and  
Peter Meinlschmidt

Fraunhofer Institute for Wood Research (WKI),  
Bienroder Weg 54E, D-38108 Braunschweig

**Abstract** Various contaminants in recovered wood, including wood treated with preservatives, limit its use for the production of particle boards due to technical reasons and, in some countries, national legislation. In order to sort them out from a stream of recovered wood, in-line detection techniques for these contaminants are necessary. The work presented here shows that NIR spectral imaging has the potential to differentiate between various organic and inorganic wood preservatives qualitatively as well as quantitatively.

## 1 Introduction

Recovered wood becomes more and more important as a raw material for particle board production in Europe. However, the amount of recovered wood used for wood based panels is quite different in the EU countries due to different national legislation. In Germany for example, recovered wood for wood based panels has to be free from thermoplastic and duroplastic polymers, PVC, coatings, foam, wood preservatives and suchlike, which is often not the case in practice. Consequently, the share of recovered wood in particle boards is only 33 % in Germany whereas it amounts to 89 % in Italy [1].

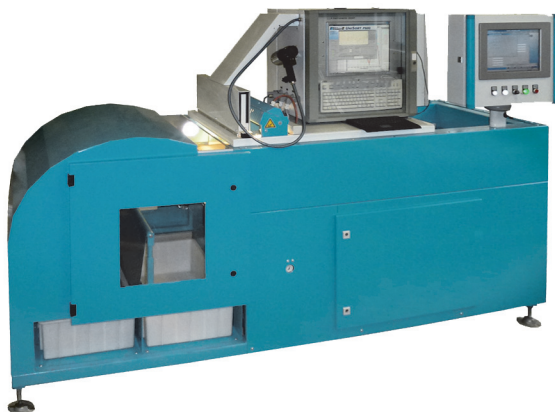
A possible way to increase the use of recovered wood for panel production is to upgrade it by sorting out the contaminants. This requires powerful in-line methods for the fast detection of the above mentioned materials. Among these, wood preservatives are most difficult to detect. In an internal research project of the Fraunhofer Gesellschaft, various methods for the detection of wood preservatives were examined,

including ion mobility spectroscopy, X-ray fluorescence, and near infrared spectral imaging. The latter is particularly interesting for sorting highly contaminated material because it allows not only the detection but also the localization and selective removal of single contaminated particles.

## 2 State of the Art

The removal of contaminants such as stones, concrete, and metals from recovered wood by physical and mechanical methods using differences in density, electrical conductivity or magnetic properties is state of art. The remaining task is to sort out contaminants which are similar to wood in the above mentioned properties. This is true for plastics and of course for wood treated with preservatives.

A possible way to sort out these remaining contaminants is to adapt commercially available sorting systems for plastics and similar materials (see fig. 9.1). To do this, it is necessary to shred the wood into chips having a size of a few centimetres and to put them on a conveyor belt. On the conveyor belt the chips pass a detection unit where the presence (and, if possible, the position) of a contaminated chip is detected. At the end of the conveyor belt a row of compressed air operated nozzles can be used to selectively remove the contaminants from the wood stream. Many different methods have been successfully applied to the detection of contaminants in recovered wood in the laboratory. Among these, ion mobility spectroscopy (IMS, [2]), X-ray fluorescence (XRF, [3]) and near infrared (NIR) spectroscopy [4] have recently proven their potential to detect organic and inorganic wood preservatives in-line. XRF is particularly suited to detect preservatives containing As, Cu and similar elements. Organic contaminants can be detected at very low concentrations in the mg/kg range by IMS. However, both techniques are not spatially resolving. This means that they can only tell the presence, but not the position of a contaminant. Consequently, one has to sort out not only the contaminant itself but some of the surrounding good material as well. This is not a problem for wood with a low level of contamination. For highly contaminated wood, however, it is necessary to remove only the contaminated chips in order to work efficiently. For such applications, a spatially resolving detection technique is mandatory.



**Figure 9.1:** Commercially available sorting system for the recycling industry (RTT Steinert)

For NIR spectroscopy, cameras with good spatial and spectral resolution are now available which makes this technique suitable for sorting applications. The advantages of NIR spectroscopy are that the method is contactless, non-destructive, free of radiation hazards, rapid and easy to use. The sample preparation is simple, if needed at all. Therefore in-line measurements are possible, enabling the implementation in an existing sorting system.

A potential challenge for NIR detection of wood preservatives is their often low concentration which can be below 0.1 % - 0.5 % and thus below the limits of detection. NIR is not known as a technique for trace analysis. On the other hand, preservatives are normally applied to the surface of wood pieces, and NIR spectra originate close to the surface. Thus, there is hope to find sufficiently strong signals. Furthermore, inorganic compounds are often difficult to detect in NIR spectra. Consequently, one important aim of the work presented here was to find out if organic and even inorganic wood preservatives can be detected in NIR spectra of recovered wood at sufficiently low concentrations so that an efficient NIR sorting becomes possible.

Sample No.	PCP	Lindane	CuCO <sub>3</sub> Cu(OH) <sub>2</sub>	H <sub>3</sub> BO <sub>3</sub>	Cu-HDO	Benzalkonium-chloride	Propiconazol	Didecylpolyoxyethyl-ammoniumborate
Holz10B	x	x						
Holz8			x	x	x			
Holz9			x	x		x	x	
Holz1D	x	x	x	x				x

Figure 9.2: Specifications of samples treated with four different mixtures of wood preservatives

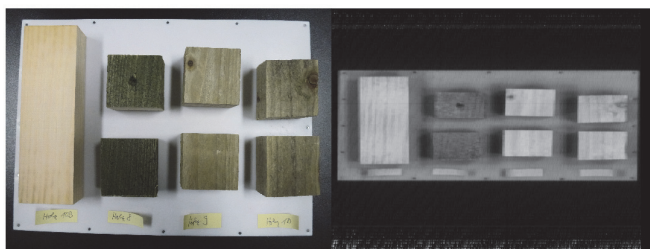
3 Experimental

NIR spectra were taken using a SpectralEye RedEye 2.2 system from inno-Spec GmbH (Germany). The system is sensitive in the wavelength range from 1100 nm to 2200 nm, has a transmissive grating and a cooled extended InGaAs detector with 256 x 320 pixels (spectral x spatial) and a frame rate of 330 Hz. Spectral images were acquired using the push-broom imaging principle [5]. Samples were scanned using a black conveyor belt at a speed of 5 m/min. In such a way, a complete spectrum for every pixel of the surface was obtained. The samples were illuminated with four halogen lamps having a power of 250 W each.

In order to increase the signal-to-noise ratio, the recorded spectral images had to be smoothed in the spectral dimension by Savitzky-Golay filtering and in the spatial dimensions by median filtering. Afterwards various chemometric techniques [6] were applied in order to reduce the data, including principal components analysis (PCA) and the PARAFAC algorithm. In some cases, additional data classification by means of Linear Discriminant Analysis (LDA) was necessary.

One surface of a number of pine wood samples with a size of a few centimetres was treated with four different typical mixtures of commercially available wood preservatives. These mixtures consist of several components. Fig. 9.2 shows which components are present in the samples, together with the sample numbers. Samples were arranged on a board as shown in the left part of fig. 9.3 and scanned as described above. The right part of fig. 9.3 shows the spectral image of the samples, averaged in the spectral dimension. The distortion in transport direction is a consequence of the specific conveyor belt speed chosen.

A second set of six pine wood samples was treated with Cu(II) sulfate only, but with various concentrations ranging from less than 1 mg Cu

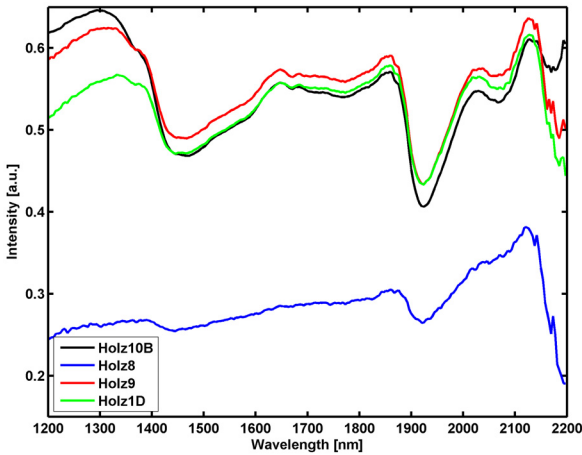


**Figure 9.3:** Colour photography and spectral image (mean intensity mapped as grey values) of the of samples

per kilogram dry mass (untreated wood) to 25390 mg Cu per kilogram dry mass. The concentrations were measured by wet chemistry.

## 4 Results

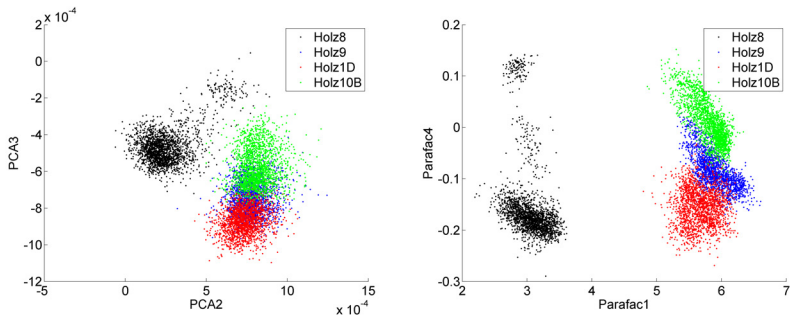
In a first step the spectral image was divided into a training set and a validation set. These sets corresponds to the lower and to the upper half of fig. 9.3, respectively. The training set was then manually segmented into regions of equal chemical composition. Reference spectra were obtained by spatial averaging over these regions. Fig. 9.4 shows the raw spectra of the first set of samples. They have different intensities, but also slightly different structures so that a discrimination of the various samples seems feasible. Especially the intensity and also the intensity variations of sample Holz8 are much smaller than in the other samples. This corresponds to the darker colour of the sample (fig. 9.3) due to the fact that it is the only sample containing Cu-HDO. Additional reference spectra were obtained for the underlying board, for the conveyor belt, and even for the paper labels (fig. 9.3). It is often recommended to get rid of intensity differences and linear trends by taking the first or second derivative of the spectra. However, intensity differences can also be regraded as additional information which helps to differentiate between samples. Furthermore, taking the derivative will amplify noise. Smoothing algorithms such as the Savitzky-Golay algorithm will



**Figure 9.4:** Raw spectra of the first set of samples

reduce this effect, but at the expense of losing spectral information. In the work presented here, we have tried all three options (raw data, first and second derivative) and obtained the best classification results for the raw data. This can be different for samples with a more complex topography and corresponding intensity differences due to shading.

In a next step, all spectra of the chemically homogeneous regions were analysed in order to check if they are close enough to the reference spectra to allow an automatic classification, or if the random variations are too big to make this possible. In order to apply standard classification methods, the typically 248 spectral intensity values for each geometrical pixel have to be condensed into a smaller number of data points. The most important methods for this purpose are the principal components analysis (PCA) and the canonical polyadic decomposition, also known as PARAFAC. Both methods were applied in this work, and a number of four components was chosen for both in order to account for at least 99 % of the data variance. Score plots were generated for every possible combination of components, and those plots were selected which gave the best clustering for spectra which belong together. These are shown in 9.5. It is apparent that the separation of different clusters is more pronounced in the PARAFAC components than in the PCA com-

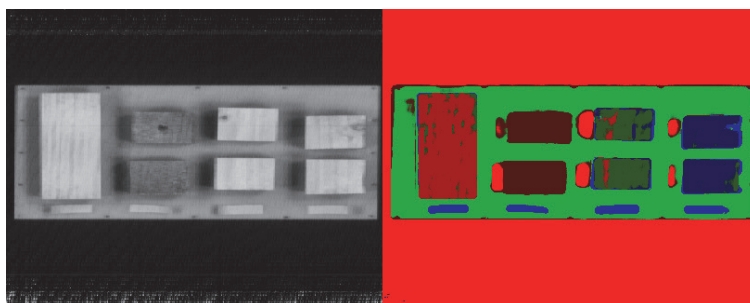


**Figure 9.5:** Optimum score plots for PCA and PARAFAC, respectively

ponents for these samples. Consequently, the PARAFAC algorithm was chosen for the next steps. This does not mean, however, that PARAFAC is generally superior to PCA. In a last step it was tested if the information obtained from the training set is sufficient to properly classify the complete spectral image (including the validation set). Although a cluster analysis by k-means could be a suitable classification method for this special case, the more general Linear Discriminant Analysis (LDA) was applied. The idea of this method is to compare every single spectrum of the spectral image to each of the seven reference spectra (four samples, board, conveyor belt, and paper labels) and put it into the same class as the reference spectrum it is most similar to. Actually, the PARAFAC components from the last step were chosen as the input for LDA rather than the spectra themselves. Taking the latter as the input gave inferior results, since the number of spectral data points per spatial pixel is too high for this method.

The result of the classification is shown in 9.6. Every spatial pixel is coded with a specific colour given by the class it was classified into. It can be seen that the complete spectral image (including the validation set) is in general classified properly. Some misclassification appears where the samples throw shadows onto the board. It is believed that this problem can be solved by standard methods of image segmentation.

The second set of samples, treated with various concentrations of Cu(II) sulfate, was analysed in the same way. For the reference spectra, a linear regression between the four principal components and the



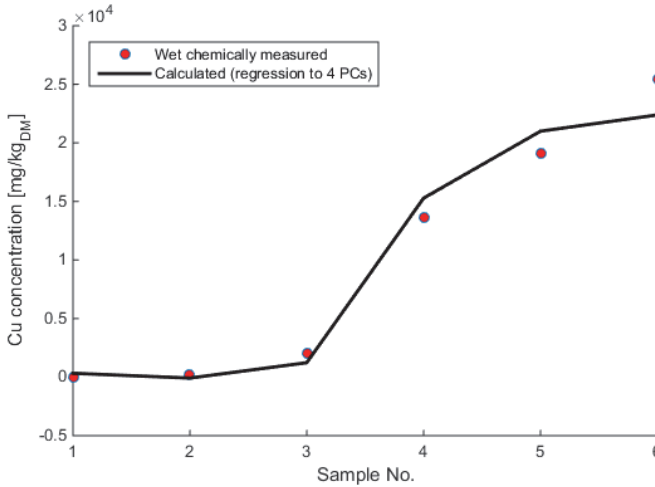
**Figure 9.6:** Classification result. Each colour corresponds to one class.

Cu concentration was made. The Cu concentrations calculated from the reference spectra using this linear regression are compared to the wet chemically measured Cu concentrations for the six samples in fig. 9.7. The agreement is quite good, with the exception of the highest concentration which is a possible outlier. In the same way, Cu concentrations could be calculated for each spatial pixel using the local spectra. The resulting concentration image is shown in fig. 9.8. Apparently, the characteristic pattern of late wood and early wood of the samples is still visible. It remains to be checked if this is a direct influence of the wood chemistry on the spectra, or if the preservatives diffuses differently into late wood and early wood, respectively.

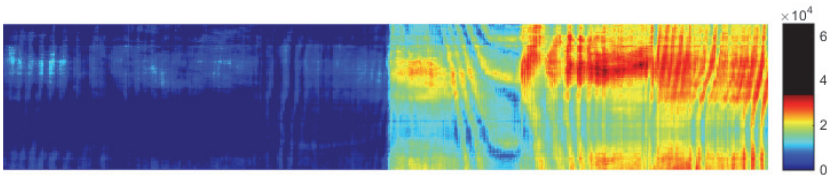
## 5 Summary and Conclusion

Pine wood samples treated with various kinds and various concentrations of wood preservatives were characterized by NIR spectral imaging. After proper data processing it was possible to classify the spectra according to the chemical composition at surface. This is true not only for organic preservatives, but also for inorganic preservatives. This is most likely the consequence of a chemical reaction between the inorganic preservative and the wood constituents. In at least the case of Cu(II) sulfate the preservative can be detected quantitatively.





**Figure 9.7:** Comparison of wet chemically measured and calculated Cu concentrations



**Figure 9.8:** Concentration image calculated from the spectral image. Values are in mg Cu per kilogram dry mass.

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