Proceedings IRG Annual Meeting (ISSN 2000-8953)

IRG/WP 19-20660

THE INTERNATIONAL RESEARCH GROUP ON WOOD PROTECTION

Section 2 **Test Methodology and Assessment**

Performance of modified wood in service - multi-sensor data fusion and its multi-way analysis

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Paper prepared for the IRG50 Scientific Conference on Wood Protection
Quebec City, Quebec, Canada
12-16 May 2019

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ABSTRACT

Recent developments in the field of electronic sensors and analytics provide new opportunity for accurate characterization of materials often based on portable and non-destructive methods. By using several complementary techniques, the material description is precise and complete. The data provided by multiple equipment, however, are often not directly comparable due to different resolution, sensitivity and/or data format. The complexity related to the data fusion step and its further interpretation often leads to not complete exploitation of the available data.
This paper presents a multi-block approach used for merging experimental data collected by measurement of modified wood in service. Characterization of samples appearance (colour and gloss) is merged with spectral data that decodes information regarding chemical composition. Alternative approaches for data fusion on the low-, mid- and high-levels are introduced, discussed and confronted with the standard approach (single sensor data interpretation). Finally, the trial to analyse the data with multi-way method is presented and interpreted.

Keywords: modified wood, data fusion, multi-sensor, multi-block, PARAFAC

1. INTRODUCTION

Recent advancement in development of scientific instruments provides numerous methods that might be used for assessment and monitoring of materials properties. Current trend is to use multiple sensors simultaneously, which is more favourable than a single sensor approach, due to more accurate representation of the reality. Selection of the optimal sensor, measurement strategy, signal processing and interpretation of results is complex and demanding (Sandak et al. 2015a). Multi-sensor monitoring generates new issues and challenges, where the strategy for merging the different sources of information is fundamental (Hua et al. 2013). Multi-sensor data fusion refers to the acquisition, processing and synergistic combination of information gathered by different sources to provide a better understanding of certain phenomenon (Varshney 2010). The driving force here is that the fusion of complementary information available from different sensors will yield increased knowledge of the investigated phenomenon, which is not attainable by any of the single sources. Multi-sensor monitoring, however, poses new issues and challenges in the data analysis phase, which can be addressed by proper data fusion strategies.

Data collected from different types of sensors are often based on diverse physical phenomena, therefore, both data integration and interpretation of results is complicated. Some sensors may be more accurate than others, since these are more sensitive in certain conditions, they may have different resolution, time scan, etc. Finally, the collected data bring shared (correlated) as well as distinctive information, which makes it necessary to interpret them altogether (Sandak et al. 2015b). In general, multi-sensors measurement generates a set of data collected by different platforms and available for the entire set of samples, with each set usually referred to as a data block. Thus, such data need to be handled by multi-block data analysis methods or other data fusion techniques. These approaches allow to jointly extract information from different blocks, which is more efficient than creating individual models. Data fusion approaches can be distinguished according to the level at which data are fused in low- (fusion of raw data), mid- (fusion of features extracted by single data block) and high-level (fusion of results/decisions derived by each data block). Multi-block methods usually operate at low-level. Moreover, a complicating factor may arise when data blocks are of different order (e.g., matrices and tensors) (Cocchi 2019).

Time series data generated within this research refers to multi-sensor measurements and are in the form of a three-way array. That is, samples are characterized by several sets of variables at different time, thus can be arranged in a data cube of dimensions samples *x* sensors *x* measuring time. In order to deal with datasets presenting more than two-dimension and showing a trilinear structure, parallel factor analysis (PARAFAC) was developed. PARAFAC operates a decomposition of the three-way array (in a similar way to PCA for bilinear data) as a sum of triple outer product of vectors, which refer to each of the modes of the array (e.g., samples, variables, time). The three sets of vectors are called loadings. The loadings referring to samples mode, in analogy with PCA, are most often called scores. Differently from PCA, the extracted components are not forced to be orthogonal, since PARAFAC allows for so-called unique models. This means that if the data follow the PARAFAC model, PARAFAC is able to uniquely uncover the underlying components. For example, if data follow Beers law, the PARAFAC loadings will be an estimation of the pure spectra, even from a mixture. In general, PARAFAC can be considered as recovering the profile corresponding to each unique phenomenon that is generating a variance source in the analysed data, such as time profile (Bro 1997).

This paper presents the results regarding performance in service of modified wood during natural weathering test. Investigated bio-materials were characterized before, during and after degradation by biotic and abiotic agents in order to provide experimental data to be used for better understanding of the bio-materials performance/degradation as a function of time and/or weather dose. A multi-sensors measurement chain allowed the acquisition of properties at different scales (molecular, microscopic, macroscopic). Data fusion results and interpretation are discussed and compared with results obtained by models based on a single sensor. Finally, a multi-way approach has also been tested and discussed.

2. EXPERIMENTAL METHODS

2.1 Experimental samples

A set of six radiata pine (*Pinus radiata* D. Don) samples representing different commercially available modification processes was selected for the demonstration. Weathering performance of these materials was compared with the not treated wood of Scots pine (*Pinus sylvestris* L.), being usually considered as a reference material (#5). The wood modification processes included: thermal treatment with penetrating oil (#1), thermal treatment with silicate treatment (#2), thermal treatment with coating (#3), furfurylation (#4), thermal treatment (#6), and acetylation (#7) (Fig.

1). All investigated modified materials are commercially available on the market (Sandak et al. 2018).

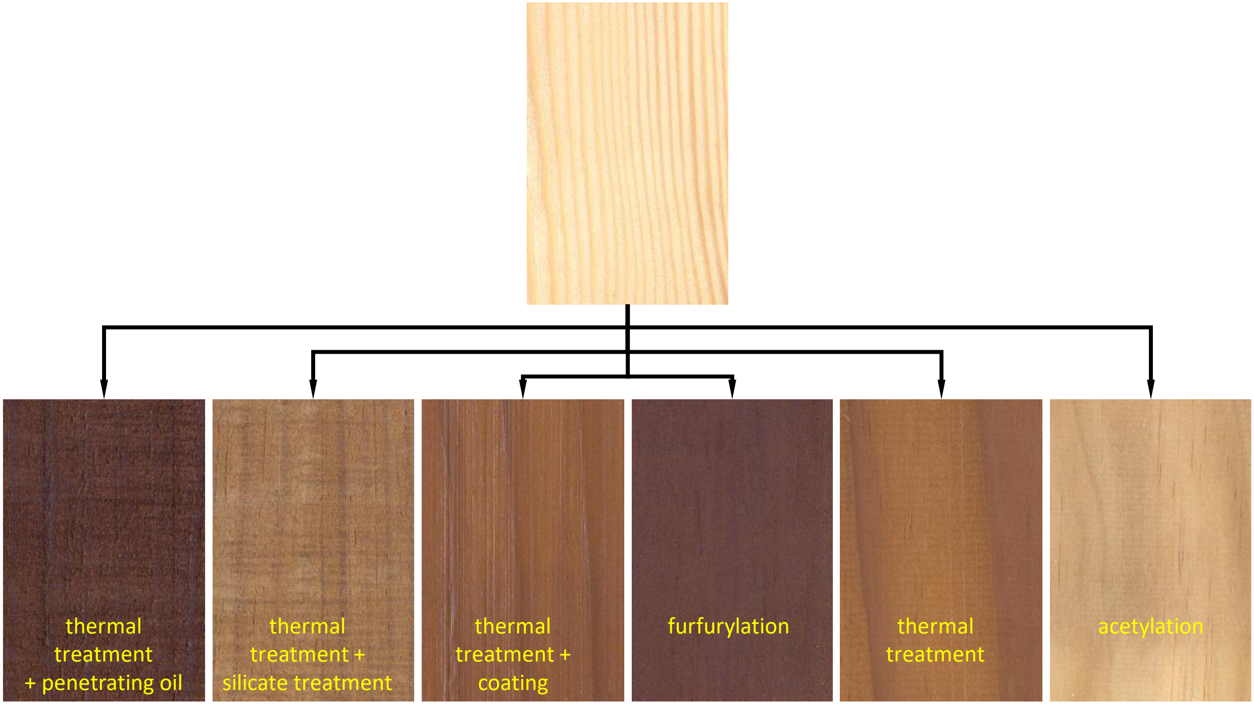

Figure 1: Appearance of experimental samples before weathering.

2.2 Weathering tests

Natural weathering tests were performed in San Michele, Italy (46°11’15’’N, 11°08’00’’E), in order to provide reference data for simulation of the bio-materials’ performance in a function of the exposure time. Samples were exposed on the vertical stands representing building façade. Stands were oriented to the four cardinal directions (Fig. 2). The weathering experiment was carried out for 12 months. Presented results refer to the southern exposure of samples, with the experiment started in March 2017.

Figure 2: Experimental samples exposed to natural weathering.

2.3 Multi-sensor materials characterization

Part of the exposed samples (three replicas per cycle) were exchanged every three months and stored in a climatic chamber before characterization. Materials characterization included measurement of the colour (CIE L*, a*, b*), scanning with office scanner in order to analyse image and to calculate RGB and HSL colour coordinates, gloss (in two cardinal fibre directions), as well as spectroscopy in NIR range.

2.3.1 Colour CIE Lab

Changes in colour were assessed by a spectrometer following the CIE L*a*b* system, where colour is expressed with three parameters: L* (lightness), a* (red-green tone) and b* (yellow-blue tone). CIE L*a*b* colours were measured using a MicroFlash 200D spectrophotometer (DataColor Int, Lawrenceville, USA). The selected illuminant was D65 and viewer angle was 10°. All specimens were measured on ten different spots over the weathered surface.

2.3.2 Colour RGB and HSL

Experimental samples were scanned with office scanner HP Scanjet G2710. The Red (R), Green (G) and Blue (B), as well as Hue (H), Saturation (S) and Luminosity (L) values were calculated globally and separately for earlywood and latewood. A custom algorithm for identification of surface colour in latewood and earlywood zones was implemented in a LabView 2018 (National Instruments, Austin, USA) software package. The location (image mask) of earlywood and latewood was determined on the basis of the grey image histogram (extreme dark and bright pixels). The RGB/HSL colour values were computed as a centre of gravity for histograms obtained from the masked areas of source colour images separately for earlywood and latewood. The print screen of the software is presented in Fig. 3.

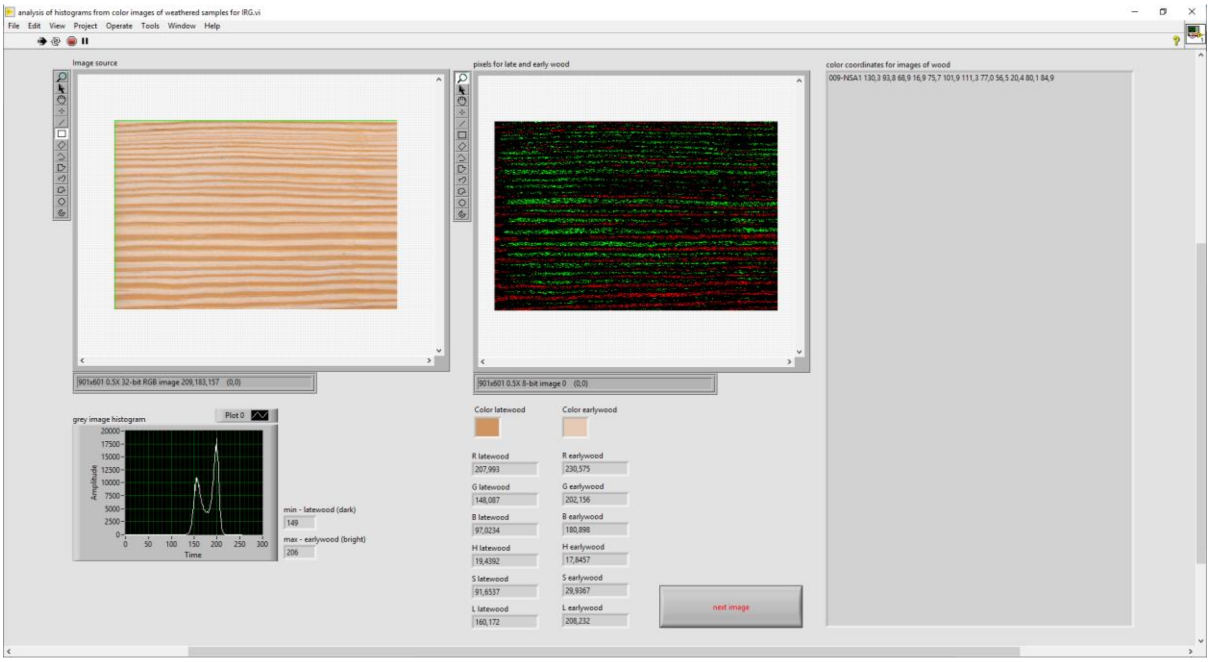

Figure 3: Print screen of the Lab View software used for image analysis.

2.3.3 Gloss

The mode of light reflection from the surfaces was measured using a REFO 60 (Dr. Lange, Düsseldorf, Germany) gloss meter with incidence/reflectance angle of 60°. Ten measurements were taken in total on each specimen, following two directions: along and across the fibres.

2.3.4 FT-NIR spectroscopy

Near infrared spectra were collected with a Vector N-22 Fourier-transform NIR spectrometer produced by Bruker Optics GmbH (Ettlingen, Germany). The system was equipped with a fibre optic probe and the measurement range was between 12000 cm^{-1} to 4000 cm^{-1} (833 to 2500 nm). The spectral wavenumber interval was 3.85 cm^{-1} with zero-filling equal to 2. The spectral resolution was 8 cm^{-1} and 32 internal scans were averaged at each spectrum. The background was measured every hour on Spectralon® resin. Three measurements were taken on each experimental sample.

2.4 Data fusion algorithm and multi-way analysis

Multi-block algorithm allowed combining multiple measurements taken on the same objects (aka samples) or over the same or similar periods of time (for a time-dependent system). The data from spectroscopic, colour, image analysis and gloss measurements were analysed with the PLS Toolbox software (Eigenvector Research, Inc.). The schema adopted for data fusion is presented in Fig. 4. All different data blocks share a common dimension corresponding to the number of samples. A mixed low/mid-level data fusion approach was applied. In fact, CIE Lab, RGB, HSI and gloss variables were simply concatenated, while the NIR spectroscopic data were compressed by PCA (retaining the four components scores as features) in order to reduce the number of variables and filter out the noise. The fused data (after autoscaling within each block) were block-scaled in order to assure equal contribution to the model. In that case each variable was weighted by its inverse standard deviation, and additionally corrected taking into account the number of variables in each block.

The experimental data represented a time series data type. Therefore, in the data fusion protocol implemented, they were unfolded variable-wise by taking wood samples and time in the sample direction. It allowed analyses with the multi-way approach, preserving their data structure and assuring the most efficient extraction of the time trends. Parallel factor analysis (PARAFAC) was identified as a suitable method for the purpose of this research. The numerical calculations were performed as well with the PLS Toolbox software (Eigenvector Research, Inc.).

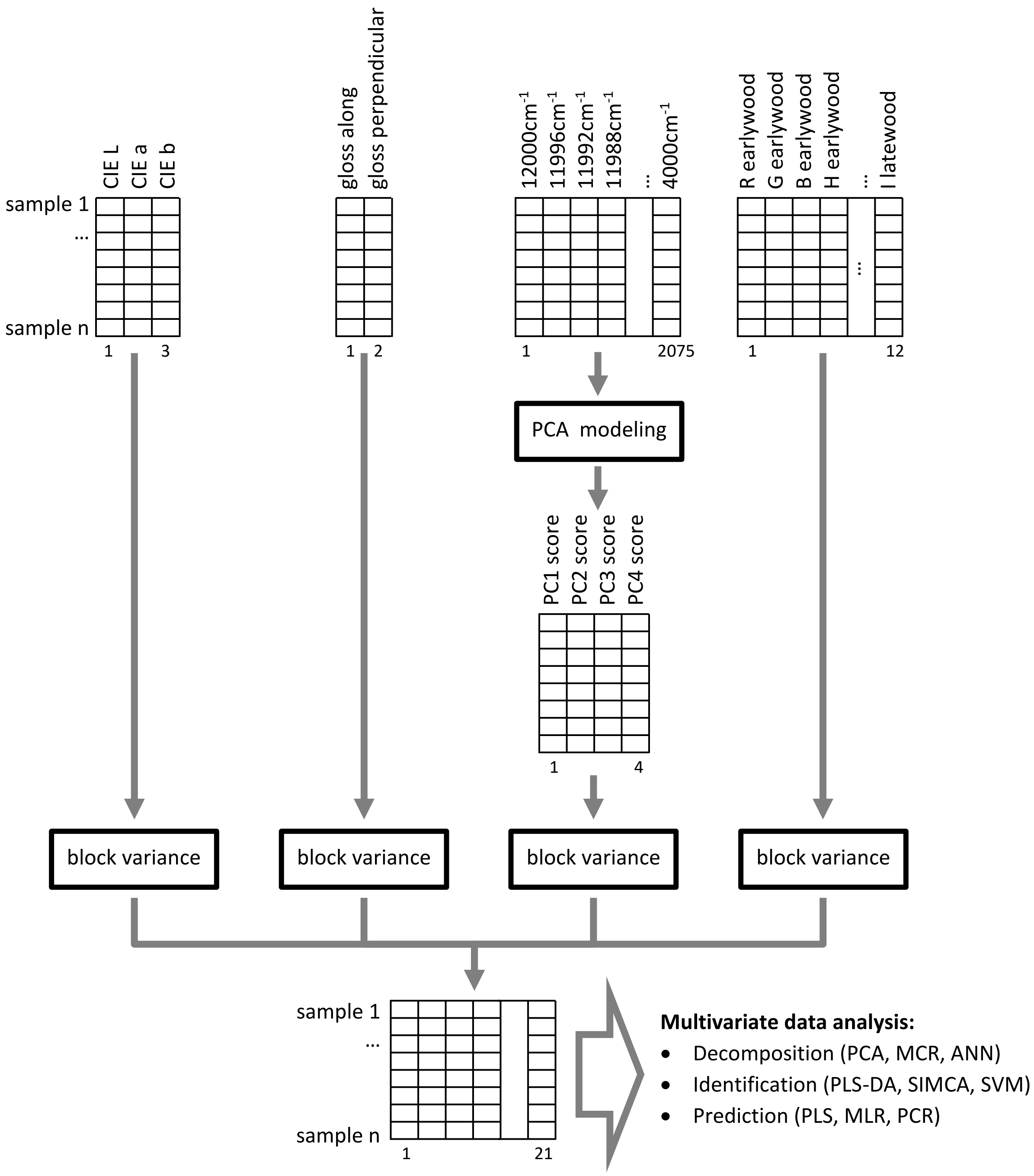

Figure 4: Concept for data fusion as implemented for multi-sensor analysis of the weathered wood surface.

3. RESULTS AND DISCUSSION

3.1 Single sensor evaluation

3.1.1 Appearance

The appearance of investigated materials in the function of time is presented in Fig. 5. Some of the materials were relatively stable regarding colour and pattern changes (#1, #3), while others (#4, #5, #6, #7) contained noticeable mould discoloration on their surfaces. Material #2 changed its original appearance after three months of exposure, with minor colour changes afterward. It corresponded to the technical description of the product, as according to the producers it was designed to silver off due to natural exposure. None of investigated materials became grey, even if the weathering test was performed for 12 months. Otherwise, the greying of wood surface is a usual response of wood to long-term exposure to weathering. An increase of gloss parameters (especially across the fibres) was noticed with the progress of the weathering process. The numerical values for CIE L*a*b*, gloss parameters and RGB calculated for the entire sample area are presented in Fig. 6.

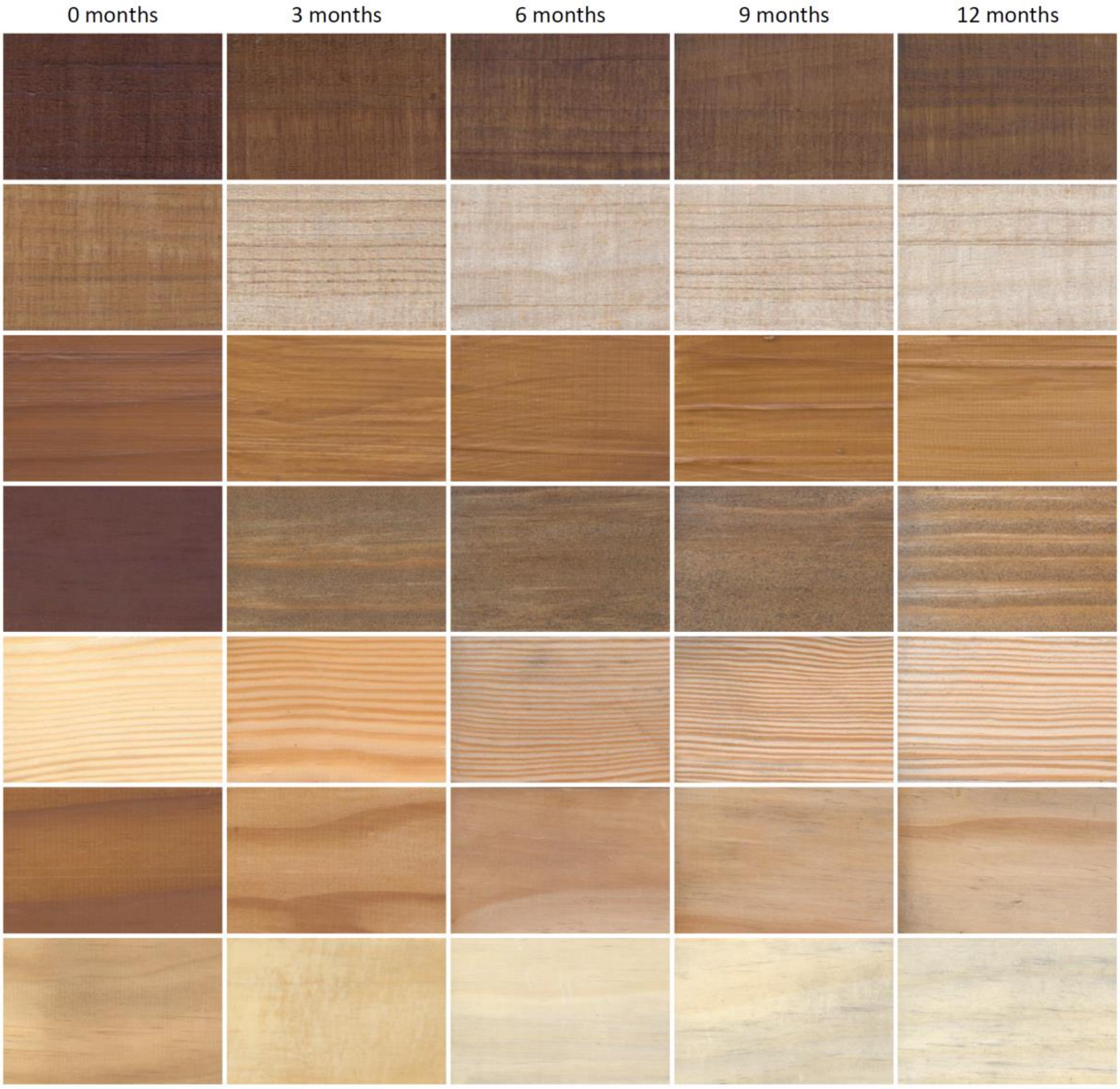

Figure 5: Change of samples appearance along one year of natural weathering (from up: #1, #2, #3, #4, #5, #6, #7).

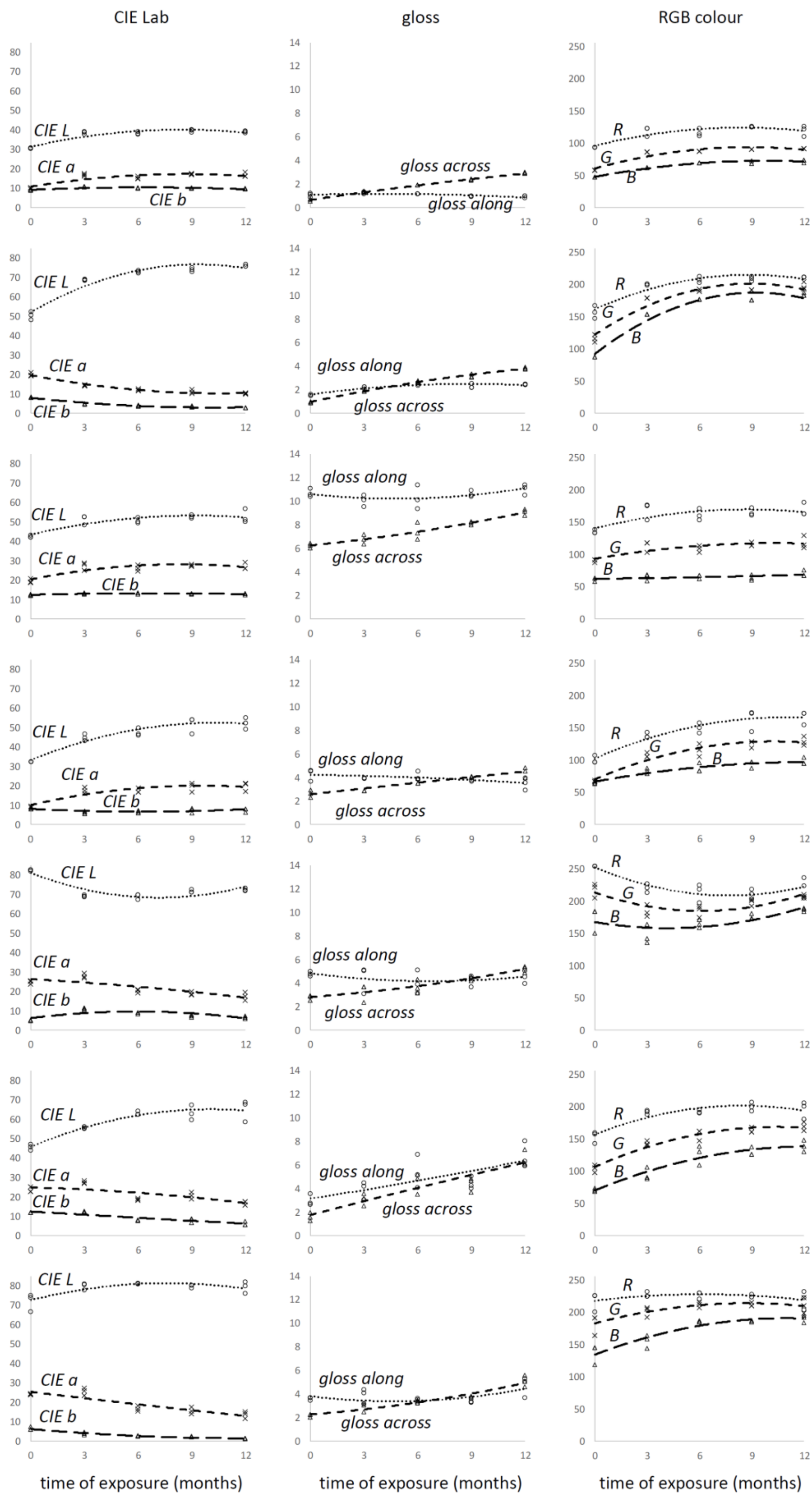

Figure 6: Change of CIE L*a*b*, gloss and global RGB parameters due to natural weathering. Note materials presented in the order from upper row: #1, #2, #3, #4, #5, #6, #7 (Sandak et al. 2018).

3.1.2 NIR spectroscopy

Analysis of NIR spectra allowed determination of the chemical changes kinetic as associated to functional groups of wood components. Bands 4404cm^{-1} and 5219cm^{-1} (assigned to carbohydrates and water, respectively) changed in all investigated materials. Changes in the band 4404cm^{-1} indicates degradation of the functional groups (-CH, -CH_2, -OH, -CO) in cellulose and hemicellulose. The reference sample (not treated pine wood) spectra revealed the highest changes for bands: 4198, 4280, 4404 and 5219cm^{-1}. The distinctive changes at 6121cm^{-1} (assigned to hydroxyl groups of cellulose) were observed only in furfurylated wood samples. The band 5980cm^{-1} assigned to -CH functional group of lignin was degraded in the case of all investigated materials, but with different extents.

The functional groups assigned to crystalline and semi-crystalline cellulose (both -CH and -OH) did not degraded due to weathering in all investigated materials. According to Kalnins and Feist (1993), the weathering leads to increases of hydroxyl concentration on the wood surface. It is confirmed by slight increase of band 7008cm^{-1}, assigned to the -OH groups in amorphous cellulose. Analysis of the specific degradation kinetics, associated with particular functional groups of wood constituents, allows better understanding of the weathering mechanisms. NIR spectroscopy is capable, therefore, to highlight week points of investigated materials that might be further improved by adjusting modification process settings.

3.2 Data fusion approach

The raw signals provided by the selected characterization methods deliver two types of data: multiple variables (values at a given type of measurement) in case of colour and gloss, as well as spectra (where series of data are representing wavenumber resolved signals) in case of NIR spectroscopy. The experimental data can be merged at different levels with various robustness and flexibility. Moreover, every block can have a specific pre-processing, including filtering, normalization or other scaling methods. In this case, for all measured parameters with the exception of NIR spectra, low data fusion has been applied. In order to handle high numbers of variables (2075 wavenumbers generated by spectroscopic measurements), PCA analysis has been carried out before data fusion. As a result, 3 CIE L*a*b* parameters, 4 PC scores, 6 RGB and 6 HSL values (calculated separately for earlywood and latewood) were provided for the data fusion (Fig. 4).

3.3 Parallel factor analysis

According to Schmitz et al. (2014), PARAFAC proved to be a suitable numerical method to reveal the structure contained in the experimental data. It enables assessment of functional relations between the recorded groups of different stimulus conditions and time structures. Fig. 7 presents an output of the PARAFAC decomposition by using two factors. The majority of the information (88.6%) was captured by factor/component 1, while factor 2 explained 4.8% of variance. The data were arranged with mode 1 corresponding to time, mode 2 to measurement and mode 3 to different wood samples (modification processes). It can be clearly seen that for all investigated samples monotonous increase with time can be noticed for component 1. It means that all the investigated materials follow certain patterns of deterioration related to progress of the weathering process. The values of component 2 show relatively less variability. Only a slight drop of the component 2 value was noticed, even if the overall trend was more persistent when compared to component 1.

Analysis of mode 2 results (component 1) reveals that the CIE L* parameter was most influenced by weathering progress. Other parameters providing important information include CIE b*, gloss (measured in both directions), RGB parameters (measured for both earlywood and latewood) as well as luminosity measured for earlywood. Four PCs calculated for NIR spectra and hue parameter measured for earlywood and latewood seems to be relatively irrelevant. However, it can be stated that PC1 and PC2 calculated for NIR spectra as well as gloss parameters provide important contribution as highlighted in component 2. Nevertheless, it has to be stated that PC2 of NIR spectra covers a relatively low percentage of the explained variance (4.8%).

Mode 3 of the PARAFAC model encodes an influence of the modification process on the weathering kinetics. It can be observed by analysing component 1 that material #1 exhibits minor changes due to weathering, contrary to material #5 and #7 (reference and acetylated pine, respectively). Analysis of component 2 revealed that material #3 (pine thermally treated and coated) as well as material #7 (acetylated pine) were the most diverse from others tested in this experiment.

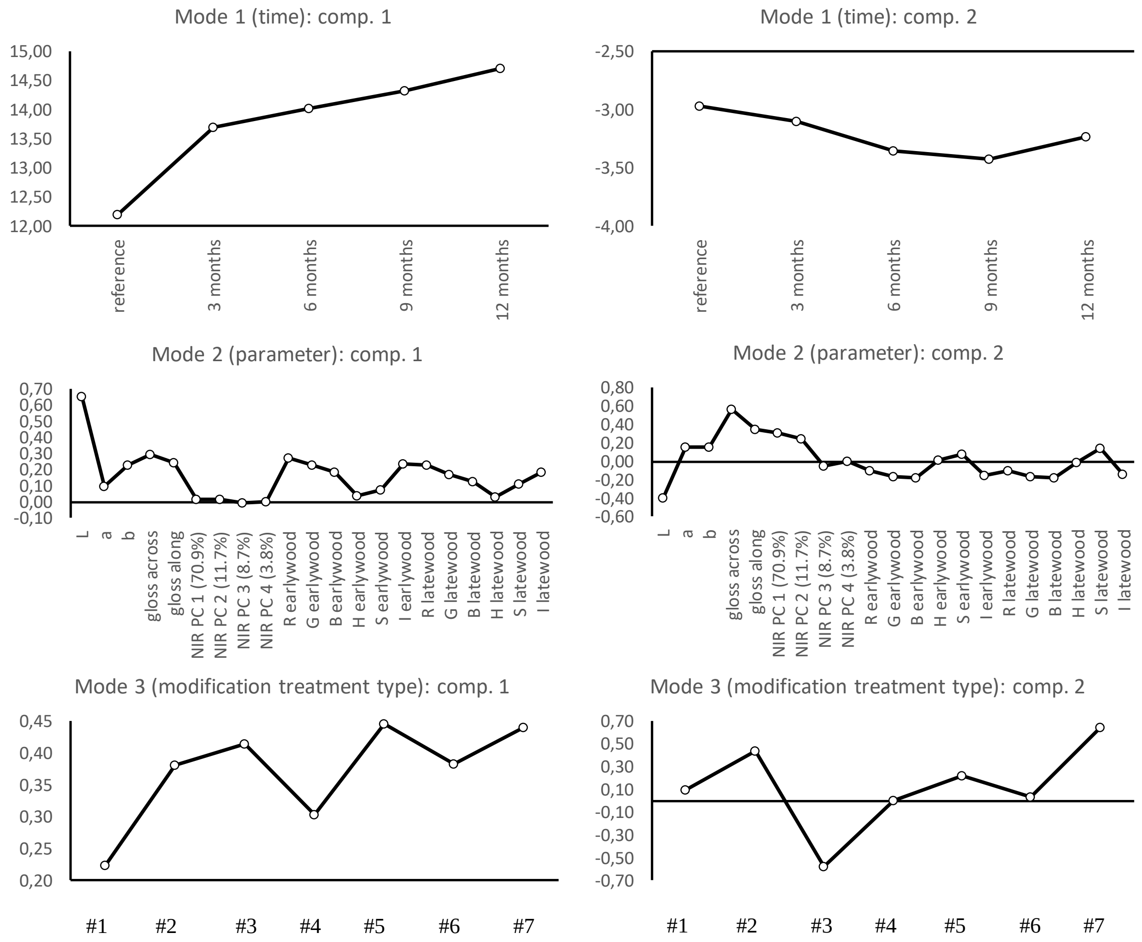

Figure 7: PARAFAC model decomposition using 2 factors. Percent variance captured by PARAFAC model: comp. 1 = 88.6%, comp. 2 = 4.8%.

PCA of fused data (Fig. 8) highlights that each treatment follows its own weathering kinetics. Even though, the trend of changes to the first principal component was similar (i.e., a monotonic increase along the exposure time). Most variation occurred during the initial three months, followed by a tendency to plateau. PC 1 scores of materials #1 and #3 present more flattened increase. The pattern of other modified materials #2, #4, #6, and #7 is much more dynamic. The varying slope of the first part of the curve indicated differences in the degradation (changes) kinetics. The only exception was noticed in the case of treatment #5 (not modified pine wood), where the value of PC1 decreased at the initial phase, followed by the increase.

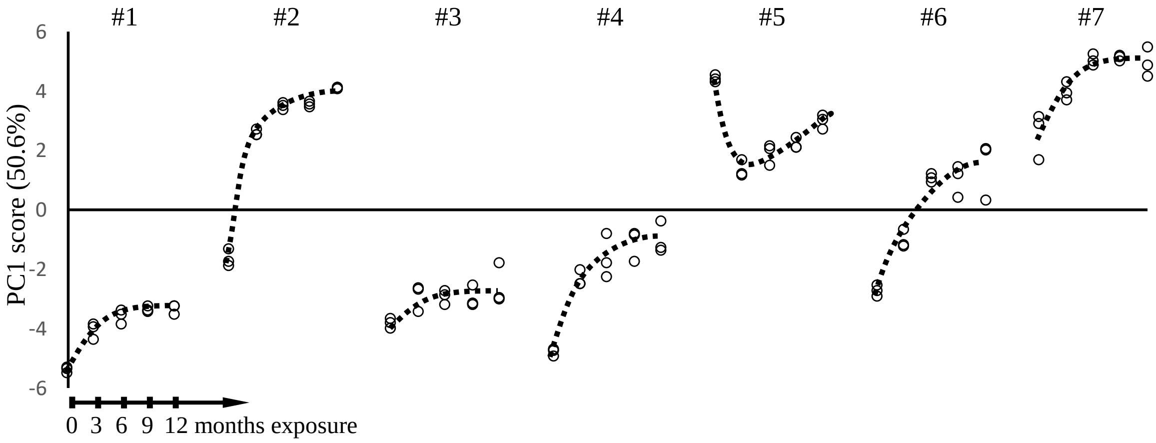

Figure 8: Score value of first principal component (explaining 51% of variance) for the PCA model of the multi-block data set for treated pine wood exposed to natural weathering for one year.

4. CONCLUSIONS

This paper presents an alternative concept for fusion and multi-way analysis of multi-sensor data related to performance of modified wood in service. Experimental samples were measured with different techniques providing information regarding their aesthetics and chemical composition in a function of time. Measurement output has been analysed and interpreted separately. Additionally, the multi-block approach was used for data merging. For all measured parameters, with exception of NIR spectra, low data fusion has been applied. In order to handle high numbers of variables generated by spectroscopic measurements, PCA analysis has been carried out before data fusion. PARAFAC analysis was performed after data merging, which allowed interpretation of time influence on measured variables and treatment method on weathering kinetic.

Presented approach for data fusion and its multi-way analysis can be applied for any kind of experimental data generated for assessment of materials performance. It allows more accurate interpretation of results and highlights interaction between influencing factors.

5. ACKNOWLEDGEMENTS

Part of this work was conducted during BIO4ever (RBSI14Y7Y4) funded within call SIR by MIUR and the project Multi-spec (BI-IT/18-20-007) funded by ARRS.

The authors gratefully acknowledge the European Commission for funding the InnoRenew CoE project (Grant Agreement #739574) under the Horizon2020 Widespread-Teaming program and the Republic of Slovenia (Investment funding of the Republic of Slovenia and the European Union of the European Regional Development Fund).

Special acknowledgments to COST FP1303, FP1407 and TU1403 for funding STSMs that contributed to the project and all BIO4ever partners for providing experimental samples.

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