

ORIGINAL ARTICLE



LIBS-ConSort: Development of a sensor-based sorting method for construction and demolition waste

Tim Klewe¹ | Tobias Völker¹ | Mirko Landmann² | Sabine Kruschwitz^{1,3}

Correspondence

Tim Klewe
Bundesanstalt für Materialfor-
schung und -prüfung
Richard-Willstätter-Straße 11
12489 Berlin
Email: tim.klewe@bam.de

¹ Bundesanstalt für Materialfor-
schung und -prüfung, Berlin, Ger-
many

² Institut für Angewandte Baufor-
schung Weimar gGmbH, Weimar,
Germany

³ Technische Universität Berlin,
Berlin, Germany

Abstract

A joint project of partners from industry and research institutions approaches the challenge of construction and demolition waste (CDW) sorting by investigating and testing the combination of laser-induced breakdown spectroscopy (LIBS) with near-infrared (NIR) spectroscopy and visual imaging. Joint processing of information (data fusion) is expected to significantly improve the sorting quality of various materials like concrete, main masonry building materials, organic components, etc., and may enable the detection and separation of impurities such as SO₃-containing building materials (gypsum, aerated concrete, etc.)

Focusing on Berlin as an example, the entire value chain will be analyzed to minimize economic / technological barriers and obstacles at the cluster level and to sustainably increase recovery and recycling rates.

The objective of this paper is to present current progress and results of the test stand development combining LIBS with NIR spectroscopy and visual imaging. In the future, this laboratory prototype will serve as a fully automated measurement setup to allow real-time classification of CDW on a conveyor belt.

Keywords

NDT, material classification, data fusion, recycling, circular economy, LIBS

1 Introduction

Closed material cycles and unmixed material fractions are required to achieve high recovery and recycling rates in the building industry. In construction and demolition waste (CDW) recycling, the preference to date has been to apply simple but proven techniques to process large quantities of construction rubble in a short time. This contrasts with the increasingly complex composite materials and structures in the mineral building materials industry. Manual sorting involves many risks and dangers for the executing staff and is merely based on obvious, visually detectable differences for separation. An automated, sensor-based sorting of these building materials could complement or replace this practice to improve processing speed, recycling rates, sorting quality, and prevailing health conditions.

Current investigations on sensor-based sorting technologies for CDW are based on the analysis of the visual (VIS) and/or the near-infrared (NIR) spectrum [1-5]. For example, bricks can be well identified with a VIS camera. Features in the NIR range allow separation of gypsum-containing components and organic materials from construction site waste. With both methods, however, the detection of composite building materials is often difficult because adhering impurities cannot be reliably detected.

The basic objective must therefore be to separate contaminants (especially building materials containing SO₃ like

gypsum) from the material mixture as early as possible to prevent further spreading. In view of the increasing heterogeneity of construction and demolition waste, this could only be achieved by automated pre-sorting within a simplified processing regime. Therefore, in addition to the above methods, laser-induced breakdown spectroscopy (LIBS) will be used to identify construction materials based on chemical information, and its suitability will be investigated as part of the project *LIBS-ConSort*.

In a LIBS-System (see Figure 1) pulsed laser is focused on the sample surface, some material is ablated, and an ionized expanding plasma is formed. The radiation emitted by the plasma is directed to a spectrograph, where the intensity is recorded as a function of wavelength. Specific line intensities provide information about the presence of chemical elements. For the quantification of the contents, system calibrations are carried out with reference standards.

The use of LIBS as a suitable basis for sorting has already been demonstrated in various application areas and materials, e.g., polymers [6], aluminum alloys [7] and other metals [8]. The advantages of LIBS for industrial application are: (i) little sample preparation required, (ii) all chemical elements measurable, (iii) short measurement times, (iv) real-time evaluation and process control, (v) non-contact measurements possible at a distance of several centimeters to meters from the sample. This makes

LIBS ideal for in-line process control. Compared to color-based optical methods, LIBS has the advantage that the chemical "fingerprint" of the material is used for classification and not only the color information of surface-near regions. An EU project [9] has already demonstrated the use of LIBS for sorting construction waste.

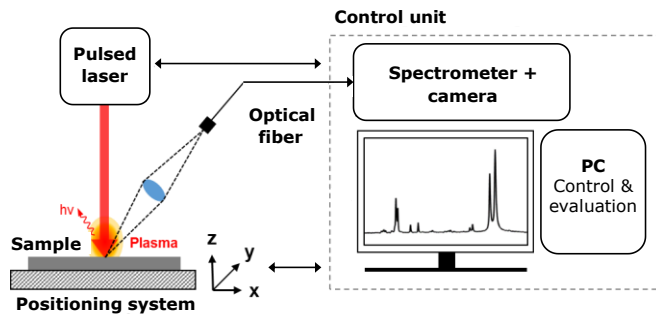


Figure 1 Exemplary schematic design of a LIBS system

2 Materials and methods

2.1 Laboratory prototype

The methodological concept to enable automated, sensor-based sorting of CDW is shown in Figure 2. Different building material fractions with a grain size of 20 mm to 100 mm are transported individually on a conveyor belt, where they are detected one after the other by the various sensors. By means of the fast camera systems (NIR and visual), an initial classification is performed, which should also detect composites and possibly define different material areas. Existing uncertainties are then reduced by locally targeted LIBS measurements in order to make the most robust estimation possible about the underlying material group(s). For data fusion, methods of multivariate data analysis and machine learning are used to achieve high recognition rates.

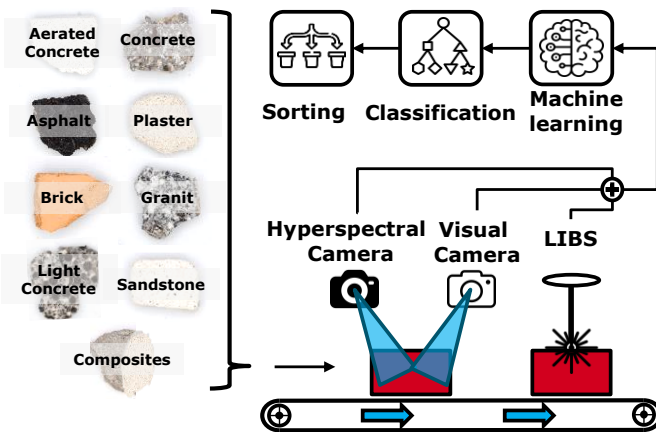


Figure 2 Methodological Concept of combining LIBS with NIR- and VIS cameras to sort various building materials in CDW.

Figure 3 shows the current progress and the associated components of the laboratory prototype. The conveyor belt is simulated with the aid of a rotating circular ring. For this purpose, a suitable drive (consisting of a stepper motor, motor driver and micro controller) was developed, which allows the desired conveyor belt speed to be set. Two hyperspectral cameras are positioned directly above the circular ring. The two models KUSTA1.7 and KUSTA2.2 from LLA instruments GmbH cover the NIR range

(900 nm – 1700 nm) and the short-wave infrared (SWIR) range (1600 nm – 2200 nm), respectively. To complete the prototype, a laser distance sensor and VIS camera will be placed between the hyperspectral cameras. In addition, a three-axis galvanometer scanner is used for the LIBS system to follow and online calculated measurement path. After all sensors are installed, a control and evaluation unit are implemented to provide automated real-time classification of various CDW materials.

2.2 Classification

To investigate the potential of a sensor combination of the NIR and SWIR camera with LIBS to discriminate different building materials, several samples were collected, which are listed in Table 1. The material groups, totalling 91 samples, are also exemplary shown in Figure 2, whereby plasters are now divided into gypsum-based plasters and other plasters (lime or lime-cement based).

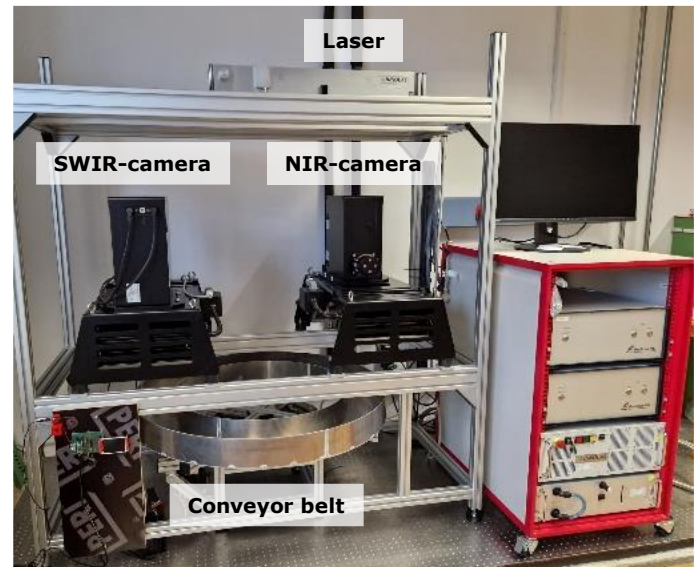


Figure 3 Under construction: laboratory prototype simulating a conveyor belt for CDW under various sensors.

Table 1 Variety and number of building materials examined with LIBS, NIR and SWIR spectroscopy.

Material group	Number of specimens
Aerated concrete	6
Asphalt	2
Brick	42
Concrete/Mortar	14
Light concrete	5
Granit	2
Plaster	3
Plaster (gypsum)	4
(Lime) Sandstone	13
TOTAL	91

All samples were measured with the camera systems shown in Figure 3. Since the LIBS system is currently still under construction, an at-line LIBS system (concrete-LIBS, Secopta analytics) was used instead. Data acquisition for LIBS data including processing steps and feature extraction have already been presented in [10].

For hyperspectral data the spectra were first smoothed (Savitzky-Golay filter) and baseline corrected (convex hull). Subsequently, the following features of the dominant absorption band are extracted: FWHM, depth, center wavelength, and continuum slope, using the PySptools library [11]. In addition, the mean reflectance was calculated over the whole unprocessed spectrum and used as a feature.

Random forest classifiers included in the scikit-learn library [12] are used to predict the material groups listed in Table 1. To avoid the overfitting scenario and simulate a realistic classification problem with unknown samples, a leave-one-out cross validation is performed: According to the total number of samples, 91 different training datasets are defined, each of which excludes a single sample, which in turn serves as test data. This is to test the ability of a trained classifier to recognize an unknown sample. Therefore, 91 models are trained and applied to their respective unknown test sample to predict the material group. This procedure is performed for each sensor (NIR, SWIR, and LIBS). The final decision of assigning a corresponding class is then based on a voting among all models, taking into account the prediction probability of each model.

3 Results and discussion

Table 2 shows the achieved accuracies depending on the sensors used. NIR and LIBS already achieve high accuracies when used alone, and correctly detect 93.4 % of samples. The differences lay in the material group-specific performance, with NIR performing more accurately with aerated concrete, granite, and plaster (lime and lime-cement), while LIBS was better at detecting concrete. SWIR showed 86.8 % accuracy, resulting from slightly poorer performance in the aerated concrete, asphalt, and light-weight concrete groups. In the case of plaster (lime and lime-cement), however, SWIR detected one more sample than LIBS and NIR with a high degree of certainty, which is why the combination of all three sensors leads to the best results.

Table 2 Achieved classification accuracy by each sensor and sensor combination.

Sensors	Accuracy in %
NIR	93,4
SWIR	86,8
LIBS	93,4
NIR + SWIR + LIBS	95,6

For a more detailed consideration, Figure 4 shows the confusion matrix for the combination of NIR, SWIR and LIBS. In the total evaluation, 95.6% of the samples were correctly identified. It is relevant to emphasize that the 100 % accuracy in the identification plasters containing gypsum is particularly relevant, whose removal from the material stream is of great importance. Due to the high lime content, there are still uncertainties with aerated concrete and the corresponding lime/lime-cement plasters, which are partly classified as (lime)-sandstone. Light concrete also shows a slightly lower detection accuracy due to its very heterogeneous structure.

	Predicted Class									True Class
	Aerated concrete	Asphalt	Brick	Concrete/Mortar	Light concrete	Granit	Plaster	Plaster gyp	Sandstone	
Aerated concrete	0.83	0	0	0	0	0	0	0	0.17	
Asphalt	0	1.00	0	0	0	0	0	0	0	
Brick	0	0	1.00	0	0	0	0	0	0	
Concrete/Mortar	0	0	0.07	0.93	0	0	0	0	0	
Light concrete	0	0	0.20	0	0.80	0	0	0	0	
Granit	0	0	0	0	0	1.00	0	0	0	
Plaster	0	0	0	0	0	0	0.67	0	0.33	
Plaster gyp	0	0	0	0	0	0	0	1.00	0	
Sandstone	0	0	0	0	0	0	0	0	1.00	

Figure 4 Confusion matrix of the performed cross validation with a random forest classifier, showing the achieved accuracies by combining NIR, SWIR and LIBS. Rows contain the true classes (black) and columns the predicted classes (blue).

4 Summary and conclusion

In this work, we presented the concept and current progress of a laboratory prototype for sensor-based sorting of construction and demolition waste by combining NIR and SWIR with LIBS. To investigate the potential and possible information gain by data fusion, the currently available systems NIR, SWIR and LIBS were used to detect different material groups using random forest classifiers. NIR and LIBS both achieved a high detection rate of 93.5 %, whereas 86.9 % of samples were correctly detected by using SWIR data. These results were improved by the combination of all systems with an accuracy of 95.6 %. It was demonstrated that merging the individual classification results based on the underlying prediction probability of the individual measurement systems is beneficial. In this way, the advantages of the individual systems could be combined.

In the context of the preliminary investigation, these results are considered promising for the laboratory prototype yet to be completed. Here, the additional information provided by the VIS camera may allow a further improvement of the detection rates. After completion of the prototype, an extended data set of test specimens and the influence of contamination and moisture on the detection accuracy will be investigated. Composite materials will also be considered separately to develop a concept for reliable identification. Finally, a real-time application will demonstrate the potential of the methodology for industrial use.

References

- [1] Müller, A. (2016) *Erschließung der Ressourceneffizienzpotentiale im Bereich der Kreislaufwirtschaft Bau*, Project report in the research program Zukunft Bau-, Stadt- und Raumforschung im Bundesamt für Bauwesen und Raumordnung.
- [2] Linß, E.; Landmann, M.; Karrasch, A.; Ludwig, H.-M.

- (2015) *Investigations on the Usability of Near-infrared Sensors for the Recovery of Coarse Aggregates from Mises Construction and Demolition Waste*, ESCC2015.
- [3] Hollstein, F.; Wohllebe, M.; Arnaiz, S.; Cacho, Í. (2016) *Challenges in Automatic Sorting von Construction and Demolition Waste by Hyperspectral Imaging*, SPIE 9862 – Advanced Environmental, Chemical, and Biological Sensing Technologies XIII.
- [4] Xiao, W.; Yang, J.; Fang, H.; Zhuang, J.; Ku, Y.; Zhang, X. (2020) *Development of an automatic sorting robot for construction and demolition waste*, Clean Technologies and Environmental Policy 22, pp. 1829-1941.
- [5] Anding, K.; Linß, E.; Träger, H.; Rückwardt, M.; Göpfert, A. (2011) *Optical Identification of Construction and Demolition Waste by Using Image Processing and Machine Learning Methods*, Joint International IMEKO TCI + TC7 + TC13 Symposium.
- [6] Costa, V. C.; Aquino, F. W. B.; Paranhos, C. M.; Pereira-Filho, E. R. (2017) *Identification and classification of polymer e-waste using laser-induced breakdown spectroscopy (LIBS) and chemometric tools*. Polymer Testing, vol. 59, pp. 390-395.
- [7] Campanella, B.; Grifoni, E.; Legnaioli, S.; Lorenzetti, G.; Pagnotta, S.; Sorrentino, F.; Palleschi, V. (2017) *Classification of wrought aluminum alloys by Artificial Neural Networks evaluation of Laser Induced Breakdown Spectroscopy spectra from aluminum scrap samples*, Spectrochimica Acta Part B: Atomic Spectroscopy, Vol. 134, pp. 52-57.
- [8] Merk, S.; Scholz, C.; Florek, S.; Mory, D. (2015) *Increased identification rate of scrap metal using Laser Induced Breakdown Spectroscopy Echelle spectra*, Spectrochimica Acta Part B: Atomic Spectroscopy, vol. 112, pp. 10-15.
- [9] Xia, H.; Bakker, M.C.M. (2014) *Reliable classification of moving waste materials with LIBS in concrete recycling*, Talanta, Vol. 120, pp. 239-247.
- [10] Klewe, T.; Völker, T.; Götz, J.; Landmann, M.; Wilsch, G.; Kruschwitz, S. (2022) *Sorting of construction and demolition waste by combining LIBS with NIR spectroscopy*, NDTCE 2022.
- [11] Therien, C. (2018), *PySptools Documentation*, <https://pysptools.sourceforge.io/>
- [12] Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; Vanderplas, J.; Passos, A.; Cournapeau, D.; Brucher, M.; Perrot, M.; Duchesnay, E. (2011) *Scikit-learn: Machine Learning in Python*, Journal of Machine Learning Research 2011.