Monitoring the sorting performance in lightweight packaging waste sorting plants using data of sensor-based sorters

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Abstract To achieve the necessary improvements in lightweight packaging waste sorting plants to increase the recycling rate, sensor-based material flow monitoring and plant control is the subject of current research and development. This study investigates whether data from existing sensor-based sorters could be used for this purpose. The results show that data recorded during sorting correlate strongly with ideal analysis data. Furthermore, a correlation between the data of the first sorter and the output fractions of later sorting stages could be established. The results therefore show a great potential for the use of sensor-based sorting data.

Keywords Monitoring, NIR, SBS, sensor-based sorting data, pixel-/object-based monitoring, lightweight packaging waste

1 Introduction

In 2019, 79.6 Mio. t [1] of packaging waste were created within the European Union (EU), marking the highest value recorded. To reduce the negative impact of packaging waste in general and plastic packaging in particular, a variety of new waste legislation measurements was presented throughout the last few years. One of them being the recycling rate for plastic packaging waste of 50% by 2025 [2]. This results in new requirements for lightweight packaging waste sorting plants to enable the aspired circular economy.

Many conventional sorting plants are currently operated as black boxes. Besides the manual analysis of input and output compositions, little process data is gathered and stored to enable plant control. However, the collection of such data is essential to find key aspects for optimization of both existing and newly built sorting plants. The research project “EsKorte” investigates not only the implementation of additional sensors for material flow monitoring but also the exploitability of existing, but not yet used, sensor-based sorting (SBS) data for material flow monitoring and control. Two research questions have been addressed with the presented analysis of SBS-data gathered during multilevel sorting of plastic packaging waste material using an experimental setup with a near-infrared sensor:

(1) Is SBS-data suitable for monitoring key sorting parameters?

(2) Is SBS-data suitable for predicting the sorting results of successive sorting steps?

2 Materials and Methods

2.1 Materials

The sample material was collected in a plastic packaging waste sorting plant in Austria. The samples taken in the output fractions were beverage cartons (BC), polyethylene terephthalate (PET) bottles, as well as containers made from polyethylene (PE) and polypropylene (PP). The samples included different brands, filling quantities and contents to represent the variety of plastic packaging waste. To ensure the best possible detection and sorting during the trials, the samples were manually cut into 3x3 cm pieces. This is due to the experimental setup requiring a reduced grain size. Caps and strongly curved particles were excluded from the sample material to ensure uniform particle properties. Three mixtures were created with the sample material (see Table 1). M1 represents an evenly distributed material, M2 a higher share of transparent PET-material and M3 a dominant polyolefin content. The corresponding pixel (px) and object (obj) shares differ due to the different area densities.

Table 1: Composition of sample mixtures (M1-M3) based on weighing (top) and corresponding average classified sensor data (bottom).

	M1				M2				M3			
	kg		wt%		kg		wt%		kg		wt%	
BC	0.507		25		0.4046		20		0.1925		10	
PET	0.507		25		0.8092		40		0.1925		10	
PE	0.507		25		0.4046		20		0.7700		40	
PP	0.507		25		0.4046		20		0.7700		40	
	px	px%	obj	obj%	px	px%	obj	obj%	px	px%	obj	obj%
BC	1073070	37	1620	33	838767	27	1232	23	403373	20	617	18
PET	1030385	35	1971	40	1644041	52	3072	57	395155	19	765	22
PE	415414	14	674	14	336186	11	542	10	619754	30	1011	30
PP	405092	14	654	13	336577	11	545	10	626035	31	1030	30

2.2 Experimental setup

The multilevel sorting was conducted with a chute sorter (working width 500 mm, length: 455 mm) using an NIR-sensor (Model: EVK Helios-G2-NIR1 [3]). The experimental setup, including the vibration conveyor for material separation, is presented in Figure 1.

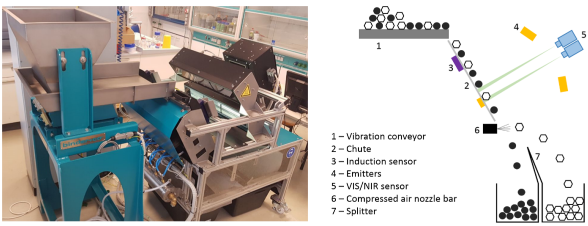

Figure 1: Experimental setup and associated schematic layout [4].

The detected pixels are 1.60 mm wide and have a length smaller than 1.60 mm (depending on the sliding speed). For the classification a teach-in was created in "SQALAR" [5]. To achieve the required classification close to 100% in each particle not only the pure materials, but also the mixed spectra resulting from labels on the objects were included. The settings for the differentiation of background and material (Spectrum Mean Intensity $\leq$ 340) were determined in an iterative process. In preliminary tests the light settings where evaluated. Lower background light caused better object localization for PET, while higher emitter light caused stronger excitation in the NIR range. The recommended default settings were altered accordingly. The reference spectra, as well as the resulting classified false color images can be seen in Figure 2.

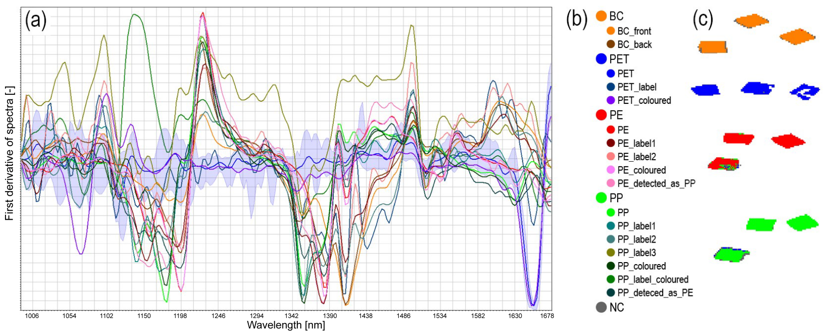

Figure 2: Reference spectra for classification (a) First derivative of reference spectra (b) Created material classes with assigned spectra (c) False colour images (orange: BC, blue: PET, red: PE, green: PP, grey: Not Classified [NC]).

2.3 Data aquisition

Each pixel is classified based on the chosen reference spectra in the software. During the trials this classification is visualized in a livestream of false colour images on a screen. Real-time data recording is achieved by using Matlab [6] to continuously scan and analyze the false-color images on the screen. The resulting values include the total number of counted pixels per material as well as the corresponding number of objects. An object is defined as an area bigger than 70 pixels of the same colour. Objects smaller than 70 pixels are typically fault detections and therefore ignored. Further the trial time and input mass for each sorting step is documented to calculate the throughput.

2.4 Experimental procedure

Each test run consists of four sorting levels (BC, PET, PE, PP), while every level includes both rougher and cleaner (see Figure 3). In a rougher, all target particles are to be sorted out, whereby the purity is low. In the cleaner, this fraction is purified by removing impurities. All input and output fractions were analysed at lower throughput to avoid overlap (Average values: rougher: 9 kg/h, cleaner: 8 kg/h, analysis: 2 kg/h). For each mixture (M1–M3) five repetitions of test runs were performed.

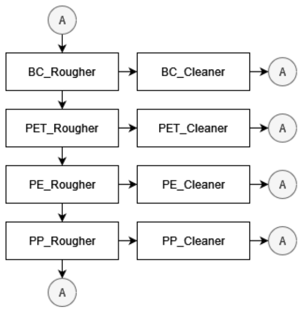

Figure 3: Flowchart of multilevel sorting; A: Analysis.

2.5 Data analysis

The data from all test runs were analysed with respect to the following parameters. x represents the number of pixels or objects. Yield_{Input} is the result in respect to the input composition, while Yield_{Level} refers to the input of the respective sorting stage.

(1) Coefficient of variation = $\frac{standard\ deviation}{mean}$

(2) $\text{Yield}_{Input} = \frac{x_{i,Eject}}{x_{i,Input}}$

(3) $\text{Yield}_{Level} = \frac{x_{i,Eject}}{x_{i,Level}}$

(4) Purity = $\frac{x_{i,Eject}}{x_{Eject}}$

3 Results

3.1 Reproducibility

Both pixel-based and object-based data was analysed to evaluate the reproducibility of data gathered from sensor-based sorters. The results show low values for the coefficient of variation (CV): $CV_{Pixel} = 0.07$, $CV_{Object} = 0.1$. The CV values increased with each sorting level, indicating a slightly better usability of sensor data from early sorting steps (see Figure 4). The higher values for NC are noteworthy, though these are also in most cases below the critical limit of $CV = 0.5$. In general, the type of material class influences the CV values more than the input mixture (see Figure 5).

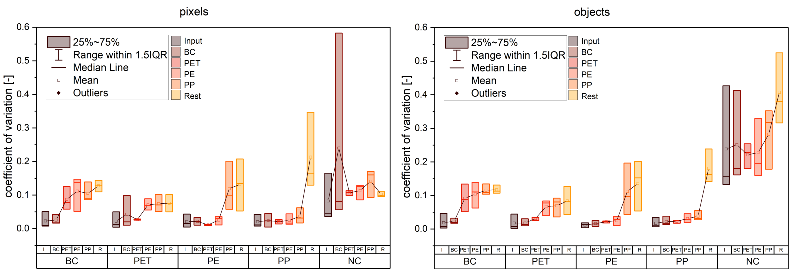

Figure 4: Coefficient of variation throughout the sorting levels. Pixel-based data (left) and object-based data (right); I: Input, R: Rest.

3.2 Exploitability of sensor-based sorting data

To assess whether the SBS data of $BC_{Rougher}$ is suitable for monitoring, a comparison was made with the input analysis data generated at optimal singulation (“ground truth”). In Figure 6 it can be seen, that the pixel data represents the ground truth slightly better than the object data. Nevertheless, the object data also shows a linear correlation and is similar to the input composition at small values.

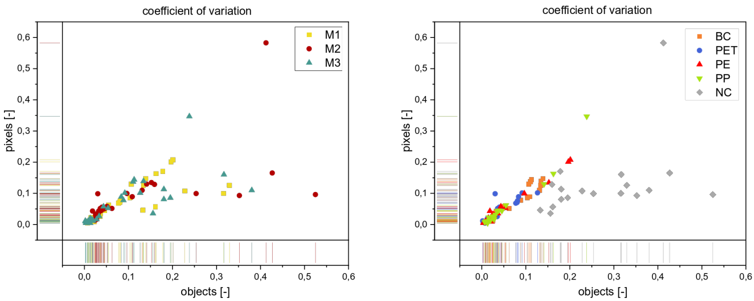

Figure 5: Influence of mixtures and materials on coefficient of variation.

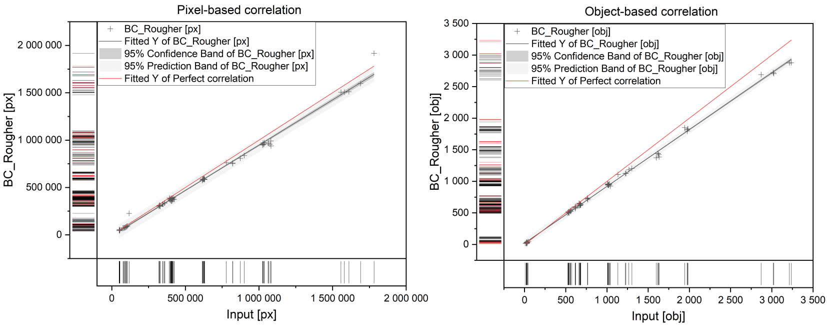

Figure 6: Comparison of Input analysis and data from SBS in $BC_{Rougher}$; Pixel-based (left) and object-based (right).

3.3 Monitoring of Yield

To determine whether the SBS data is suitable for monitoring, the yield was assessed in relation to the input as well as in relation to the respective sorting stage (see Figure 7). There is no continuous correlation between input composition and yield but clusters depending on the sorting level were discovered. The best values are for BC, followed by PET. For $Yield_{Input}$, the values for PE and PP are usually around 45 – 60 px%, from which it could be deduced that the input-related yield drops sharply from the third sorting stage onwards, regardless of material. In contrast, the sorting level-related yield (Figure 7: right) shows a clearer distinction between PE and PP. The low values of PE result from a poorer discharge behaviour, which could be observed during the tests. In general, at least a rough prediction of yield based on SBS data generated in the first sorting step appears to be possible.

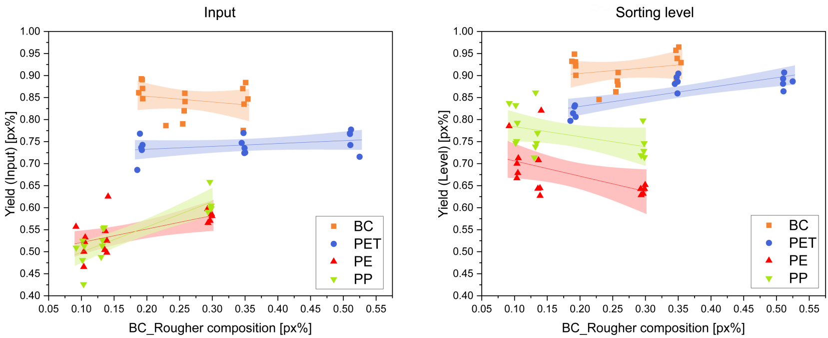

Figure 7: Yield depending on $BC_{Rougher}$ composition. Pixel-based values in relation to input (left) and respective sorting stages (right).

3.4 Monitoring of Purity

Since the purity of output fractions is a relevant criterion for recyclability, its monitoring with SBS data was further investigated. Figure 8 visualises that the composition of mixture (M1-M3) is more important than the sorting level, since there is no gradient along the sorting levels within a mixture. Lower limits and averages are higher for object-based values, which might be because pixel-based purity is degraded by misclassifications at the edges of particles.

The proportion of the target fraction increases with the purification steps (see Figure 9), which is plausible since it reflects the behaviour of sorting plants. The values of the input analysis (black) and the values of $BC_{Rougher}$ (red) are very similar, while in the eject of the rougher (purple) the purity increases strongly. The purity of the output fractions, i.e. the cleaner eject (blue), is the highest and usually has the smallest range. The correlation with $BC_{Rougher}$ data for all output fractions has a maximum range of 10.6 percentage points. This includes results for the fourth sorting level.

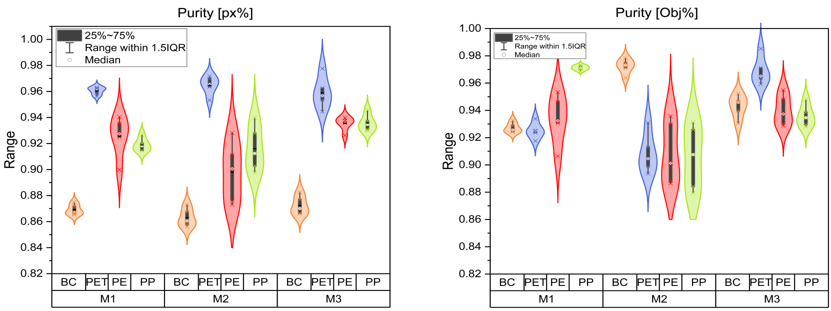

Figure 8: Dependence of purity on mixtures (M1-M3) and sorting levels (BC, PET, PE, PP); left: pixel-based, right: object-based.

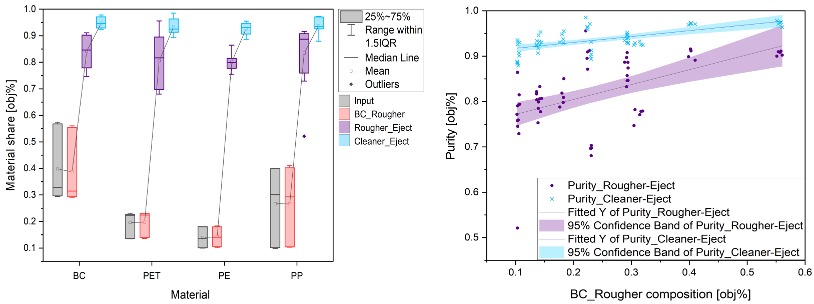

Figure 9: Increasing material shares [obj%] with increasing sorting level (left) and dependence of purity [obj%] in output fractions on $BC_{Rougher}$ composition (right).

4 Conclusion

The data presented demonstrates that SBS data has high potential for material flow monitoring. The data shows a low variation with repetition and a strong correlation between the results of the optimally singulated analysis and the data recorded during sorting. Based on the data of the first sorting stage (BC), a clear distinction of the yields of the different sorting stages is possible. Furthermore, there is a clear correlation between the $BC_{Rougher}$ data and the resulting purity of the output fractions. Based on these results, further investigations can be made to not only monitor but predict the sorting performance.

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