

Influence of surface roughness and surface moisture of plastics on sensor-based sorting in the near infrared range

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Abstract

In the project ‘NEW-MINE’ the use of sensor-based sorting machinery in the field of ‘landfill mining’ is investigated. Defilements pose a particular challenge in the treatment and sorting of plastics contained in landfills. For this reason, the effects of various pollutants caused by the interactions in the landfill body or the mechanical treatment steps in landfill mining are examined. In the following elaboration, the focus is on the influences of surface moisture and surface roughness of plastics on sensor-based sorting by means of near-infrared technology. Near-infrared radiation (NIR) in a wavelength range of 990 nm to 1500 nm has been used for the detection and classification of plastic particles. The experiments demonstrate that increased surface roughness reduces signal noise and thereby improves the classification of both spectrally similar and transparent plastics, but reduces the yield of low-softening plastics because their sliding speed on a sensor-based chute sorter varies as a result of the heating of the chute. Surface moisture causes the absorption of radiation from 1115 nm (high density polyethylene [HDPE], linear low density polyethylene [LLDPE], polyethylen terephthalate [PET] and polyvinylchloride [PVC]) or from 1230 nm (low density polyethylene [LDPE], polypropylene [PP] and thermoplastic polyurethane [TPU]) up to at least 1680 nm, which causes amplification or attenuation of various extremes in the derivative. However, the influence of surface moisture on the yield of plastics is usually very low and depends on the spectral differences between the different plastics.

Keywords

Sensor-based sorting, hyperspectral imaging, near-infrared spectroscopy, influence of defilements, surface roughness, surface water

Introduction

Sensor-based sorting units have been used for years in the recycling industry to solve complex sorting tasks. The development of modern sorting technology was initially influenced by the fields of mineral processing and food inspection (Huang et al., 2008; Wotruba and Harbeck, 2010). In contrast to the use of sensor-based sorting machines in the food or mining sector, the material flows in the recycling industry, especially in landfill mining, are characterised by significant contaminations (Maul and Pretz, 2016). These could be caused by fine mineral or biodegradable waste particles contained in municipal solid waste (MSW) (Vujić et al., 2010) or owing to impact factors of storage (e.g. water ingress by rain). Thus, the surface of objects can, among others, be covered with water, dust, grease and oils. In the past, the common doctrine was that the prerequisite for successful sensor-based sorting is a clean and dry surface. Therefore, the recycling technology had to evolve enormously to achieve the goal of producing quality-assured products from waste (Pretz and Julius, 2008; Schug et al., 2007).

A relevant advantage of sensor-based sorting units is the fact that they work non-destructively and have very short measuring times (Eccher-Zerbini, 2005). Since a high material throughput is indispensable in recycling plants, optical in-line measurement, in

particular with near infrared radiation (NIR) measurement technology, are state-of-the-art today. NIR spectroscopy is based on changes in dipole moments creating absorption bands in specific spectral regions. Position and intensity of absorption bands are influenced by molecular composition as well as intramolecular interactions. This allows for conclusions regarding both chemical and physical properties (e.g. crystal structure, density, viscosity and particle size in pulverulent solids) without the necessary sample preparation one usually needs for traditional chemical analysis (Blanco and Villarroya, 2002). Additionally, a NIR sensor is simple to operate after the initial calibration (Büning-Pfaue, 2003).

Another advantage is that, within optical sorting techniques, the sorting criterion is decoupled from the separating force. The separation criteria can be modified so that different characteristic

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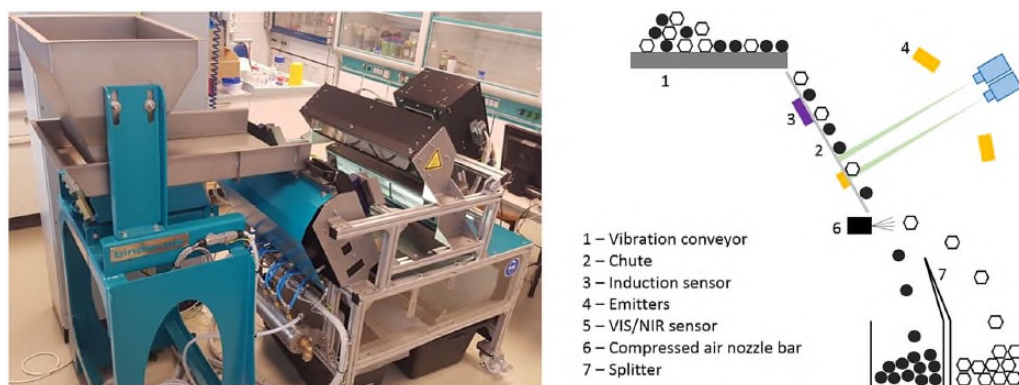


Figure 1. Test stand for sensor-based detection (left) and schematic drawing of the working principle and sensor arrangement (right).

properties of the material are decisive for the sorting decision. As a result of this decision, which is determined by the applied algorithm, the corresponding particle is discharged. Although also X-ray transmission (XRT) (Mesina et al., 2006), X-ray fluorescence (XRF) and laser-induced breakdown spectroscopy (LIBS) are used, common sensor-based sorting systems for sorting of plastics work with NIR technology (Gundupalli et al., 2016). Information obtained from photon-matter interactions (e.g. reflection, absorption, scattering and delayed re-emission of photons) at the particle surface in NIR spectroscopy is used to draw conclusions about the type of plastic enabling sorting decisions (Gschaider and Huber, 2008).

It is well known in the industry that moisture has a negative impact on the identification of materials via NIR technology in sorting plants. Additionally, it is obvious that surface roughness varies significantly depending on the mechanical preprocessing, but no studies on its impact on NIR sorting have been conducted yet. Therefore, the impetus of our research is to enable the improvement of the identification of materials by NIR spectroscopy by providing deeper understanding of the impacts on these surface properties.

In order to be able to qualitatively assess the sorting of different material streams despite contamination, it is necessary to know how the respective contaminants influence the spectrum. The aim of the present study is to evaluate the influence itself and the resulting impact on the sorting decision. The potential of such information may enable optimisations concerning plant designs and therefore improved machine efficiencies. Likewise, the algorithm for sorting particles can be adapted to take into account how different contaminants influence the detectable spectrum of a substance in the NIR range. Despite the importance of the influence of contaminations being well-known, no systematic research has been conducted yet to our knowledge. Consequently, we present the first scientific study covering the effect of surface roughness and moisture on NIR sorting of plastics.

Materials and methods

To investigate the influences of surface moisture and surface roughness on both the spectral information and the efficiency

(i.e. yield and purity) of a sensor-based sorting unit, experiments were carried out with different types of plastic.

A test stand for sensor-based detection and sorting (compare Figure 1) was used for the experiment. In addition to a colour sensor and an induction strip, it contains a NIR sensor (EVK-Helios-G2-NIR1). For the presented experiments only the NIR sensor was used. The working principle of the test stand can be seen in Figure 1. The emitter is a halogen lamp. The emitted radiation interacts with the near-surface molecules of the particles and is reflected, absorbed and/or transmitted depending on the chemical composition and structure of these particles. The dispersedly reflected radiation strikes the NIR sensor and is detected. Subsequently, this radiation (wavelength range 990 nm–1680 nm) is converted into an electrical signal. The spectral resolution of the sensor is 3.18 nm. A spatial pixel is 1.60 mm wide owing to the geometry of the experimental setup. Depending on the sliding speed of the particle on the chute, the length of the pixel may vary but is always smaller than 1.60 mm. The frame rate of the line sensor is always 476 Hz, with an exposure time of 1800 μ s.

To evaluate the influence of contaminants, various series of experiments were carried out. These can be divided as follows.

1. Influence of contamination on the detected near-infrared spectrum.
2. Influence of contamination on classification and yield of plastics.

For the series of tests for both of these aspects, eight different types of plastic were used (see Table 1). Despite the polyethylene terephthalate (PET) and polyvinylchloride (PVC) samples (originating from PET bottles and PVC film) all test specimens were specifically produced via an extrusion process at the Chair of Polymer Processing, Montanuniversitaet Leoben, and subsequently cut into particles with a projection area of approximately 25 cm².

To determine the influence of contaminants, a sorting recipe was created. From the listed materials, example objects were selected to take pictures with the NIR sensor. These recordings contain an NIR spectrum assigned to each object pixel. In order

Table 1. List of the plastics used for the test series.

Name	Abbreviation	Colour
High density polyethylene	HDPE	Grey
Low density polyethylene	LDPE	Red
Low density polyethylene	LDPE	White
Linear low density polyethylene	LLDPE	Turquoise
Polyethylen terephthalate	PET	Green/blue transparent
Polypropylene	PP	Pink
Polyvinylchloride	PVC	Clear
Thermoplastic polyurethane	TPU	Yellow

Table 2. Preprocessing and spectral processing of spectra for classification.

Preprocessing	Spectral processing
<ul style="list-style-type: none"> • Spatial correction • Bad pixel replacement • Intensity calibration • Noise suppression 	<ul style="list-style-type: none"> • 1st derivative • Normalisation • Smoothing

to be able to store a material specific NIR spectrum, at least 60 spectra per material were selected generating an averaged spectrum. The object pixels used for this purpose were grouped in clusters and selected. Care was taken to ensure that the spectra were not located close to atypical object edges or at exceptionally high/low reflecting points. The averaged spectrum serves as a reference spectrum for assigning objects to the substance classes stored in the recipe.

To detect and evaluate all potential changes, the whole spectral range within 990 nm–1500 nm was used for the classification of object pixels. Before the classification of such a spatial pixel, the detected spectrum is pre-processed and spectrally processed (Table 2):

Based on the created recipe, the individual object pixels of particles are classified and provided with false colours. If none of the taught average material spectra fits the NIR spectrum of the object pixel, it is classified as ‘not known’. In this way the image information from the NIR spectrum is classified and thus presented in a simplified version. In addition, the data volume of the spectral information is reduced, enabling fast classification of the objects.

The false colour pixels are used to assign each object to one of the taught material types. For this purpose, the classified object pixels of each material class are added up. Each object is assigned to the material class that prevails in this object. For example, in Figure 2, some high density polyethylene (HDPE) particles are partly misrecognised as PET (white pixels), linear low density polyethylene (LLDPE) (green pixels) or ‘not known’ (yellow pixels). Reasons for misrecognition may include, but are not limited to, polarisation effects. Owing to the large number of HDPE pixels (grey), the particles are correctly classified as HDPE anyway.

As mentioned above, two main aspects were examined in the experiments. To gather information concerning the influence of contaminations on the detected near-infrared spectrum (‘Aspect 1’)

the plastic particles were either roughened via a ‘Bosch PEX 220 A’ random orbital sander equipped with P60 sandpaper or wetted with, on average, 0.76 g water per particle. By usage of the random orbital sander, a severe degree of surface roughening that is expected to be either representative or even exceed the roughening degree a plastic surface can reach during mechanical processing (shredding, mechanical label removal, screening, etc.), was attained. Subsequently, spectral images of the objects (original/rough/wet) were taken to illustrate the influence of the ‘surface roughness’ and ‘surface moisture’. By comparing the spectra of soiled and clean object pixels, the influence of the respective contamination can be determined.

For the evaluation of the influence of contaminations on classification and yield (‘Aspect 2’), the plastics listed in Table 1 were sorted. Fifty particles of each material were scanned individually and discharged with compressed air (3 bar). Misses could be attributed to misrecognition or mechanical errors (e.g. different sliding speeds of the different types of material). These experiments were carried out at thresholds between the arbitrary units 10 and 100, with higher thresholds allowing larger deviations of the considered spectrum from the taught spectra for classification. Both the particle-related output (yield) and the number of correctly and incorrectly classified pixels were recorded.

Additional UV/VIS/NIR measurements were performed using a Lambda 950 ultraviolet (UV)/visible spectrum(VIS)/NIR spectrometer with integrating sphere (Perkin Elmer, Waltham, USA). Spectra were recorded from 250 to 2500 nm in 5 nm steps. The Spectralon-coated Ulbricht sphere had a diameter of 15 cm. Hemispherical as well as diffuse transmittance and reflectance spectra were used to evaluate the effect of surface roughness (Figure 3).

Results and discussion

In this section, obtained results of the influence of water and surface roughness on the detected NIR spectra are presented and discussed, followed by an evaluation of this impact on the classification and yield.

Influence on the detected NIR spectra

Surface roughness. The influence of increased surface roughness can be summarised in three observations.

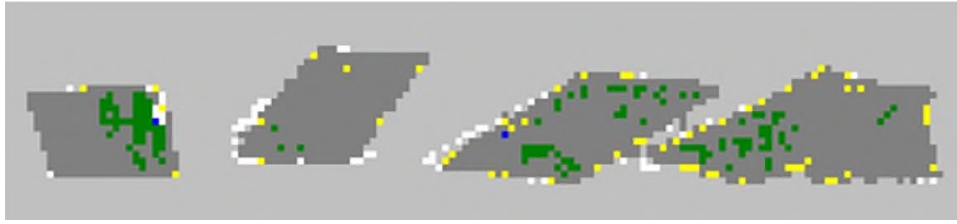


Figure 2. Correct classified HDPE particles (grey), including partially false classified pixels as PET (white) or LLDPE (green) and unknown pixels (yellow).



Figure 3. Measurement of direct, hemispheric and diffuse transmittance.

1. The intensity of the raw spectrum detected by the sensor is increased for all plastics except HDPE.
2. Extrema in the raw spectrum are amplified.
3. The spectral variation decreases owing to roughening of transparent particles.

A higher intensity of the detected raw spectrum is characterised by a better ‘spectral data basis’ per pixel. Owing to the higher amount of radiation detected per time interval, a better-founded set of spectra is created for each object pixel. This could also be proven in laboratory experiments, whereby the largest effect was observed with transparent plastics. Thus, the diffuse reflection of transparent PVC could be increased by almost 500%, while the direct reflection was reduced by 95%, from 5.9% to 0.3%.

The larger extremes in the raw spectrum, of for example PET, have the consequence that there are fewer fluctuations in the normalised derivative, relevant for the sorting decision (Figures 4 and 5). This relationship ensues from the fact that the normalisation of the spectrum is performed with respect to the absolute minimum and the absolute maximum of the spectrum. A raw spectrum, with a small difference between the absolute minimum and the absolute maximum, is stretched more than it is in the case of a large difference. Therefore, a smaller difference results in larger fluctuations in the derivative.

Surface moisture. Surface moisture has two different influences on the detected spectrum of the examined plastics.

1. Absorption of the reflected radiation starting from 1115 nm (HDPE, LLDPE, PET, PVC) or from 1230 nm (low density polyethylene (LDPE), polypropylene (PP), thermoplastic polyurethane (TPU)).
2. (Partial) smoothing of the raw spectrum.

Exemplarily, the PP spectra (with and without surface moisture) as well as the associated derived, smoothed and normalised

spectra are shown in Figure 6. It can be seen that the ‘raw spectrum wet’ has a generally lower intensity. From a wavelength of about 1230 nm on, the intensity of the spectrum continues to decrease in comparison with the ‘raw dry spectrum’. This is owing to the increased absorption of the radiation owing to surface water. Similar effects can be observed in food with high water contents. The strongest absorption of pure water samples is at 1400–1410 nm (Büning-Pfaue, 2003).

The increasing absorption of the radiation with increasing wavelength has the consequence that individual extremes in the derivative are formed stronger or weaker (see Figure 3: Ranges 1, 2 and 4). The larger the slope at the inflection point of the raw spectrum in the marked areas, the stronger the corresponding extremum which is formed in the derivative. As a result, the extremum at 1360 nm (Point A) no longer represents the absolute minimum, as it is the case with the ‘derivative normalised dry’, but the extremum at 1140 nm (Point B). Thus, a reduction of the minimum at 1360 nm takes place during normalisation.

In addition, in ‘Range 3’, a smoothing of the raw spectrum owing to the influence of water can be observed. As a consequence, the extrema of ‘derivative normalised wet’ are attenuated in comparison with the ‘derivative normalised dry’.

Influence on classification and yield

In order to investigate these results with regard to their significance for the sorting, the influence on classification and yield of both types of contamination were examined.

Surface roughness. The following observations concerning the influence of surface roughness were made.

1. Neither the classification nor the output of most plastics is significantly affected (exceptions: TPU and LDPE_red/white).
2. The number of detected object pixels of the PVC and PET particles has increased.

Since the influence of surface roughness hardly changes the raw spectrum of most plastics, the influence on the classification is very low. Only the classification and yield of transparent plastics (PET and PVC) at low thresholds (≤ 30) is improved, as the fluctuation ranges of the derived spectra are significantly reduced. Relevance for sorting therefore exists primarily if such materials need to be distinguished from materials that generate a coinciding

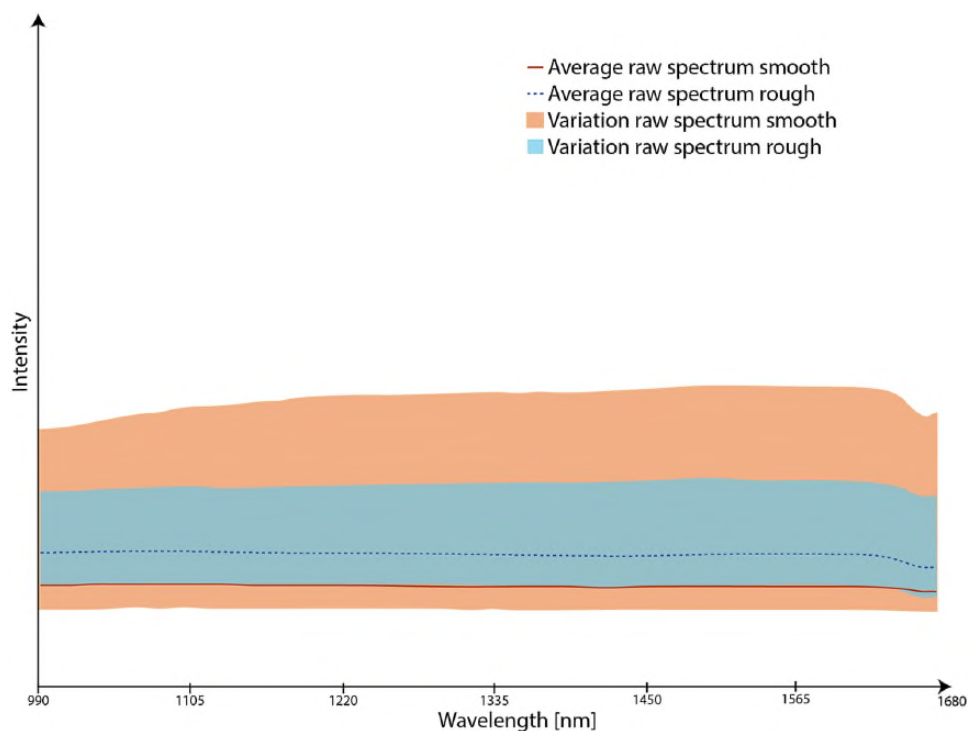


Figure 4. Average raw spectra and variations of PET spectra, rough and smooth in comparison.

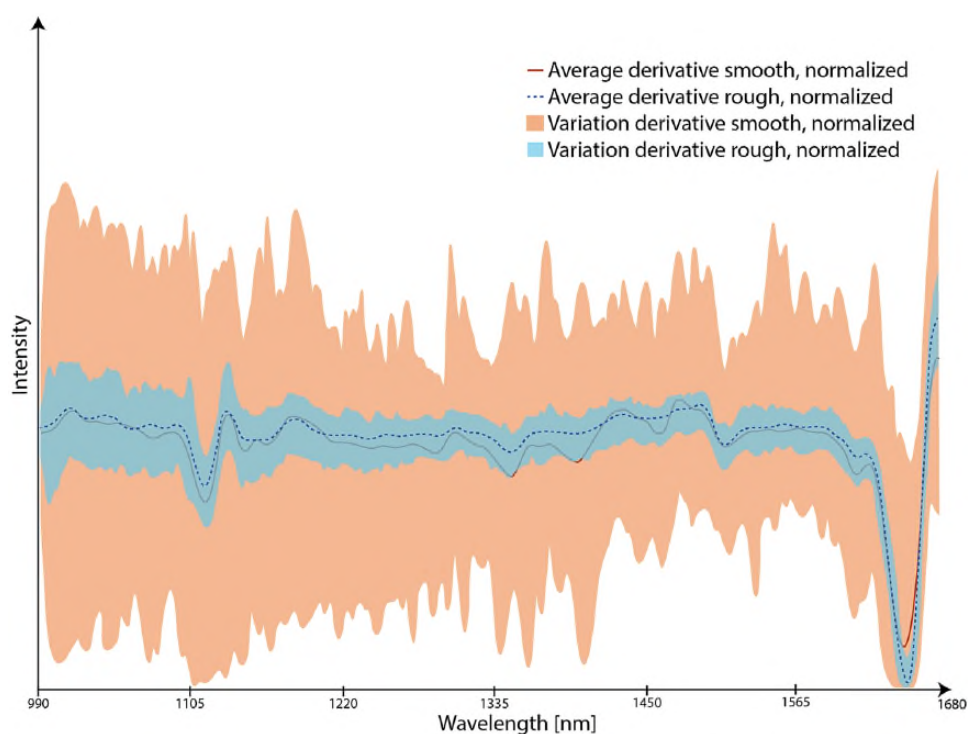


Figure 5. Average derivatives and variations of PET spectra, rough and smooth in comparison.

NIR spectrum, for example when differentiating between different types of PET.

In contrast, the results for roughened TPU and LDPE_red/white are impaired. The reduced yield of TPU particles is caused by two main factors: First, the misrecognition of roughened TPU pixels as PP is above a threshold of 30 at about 8.3% (rough)

instead of 1.0% (smooth). As a consequence, the maximum yield is reduced from 99.2% to 94.7% (Figure 7).

Second, it has been observed that the yield of TPU is temperature dependent. The surface of the chute (see Figure 1) was heated up to 58 °C by the infrared radiation. In the course of this warming, despite the constant recognition of the correctness of

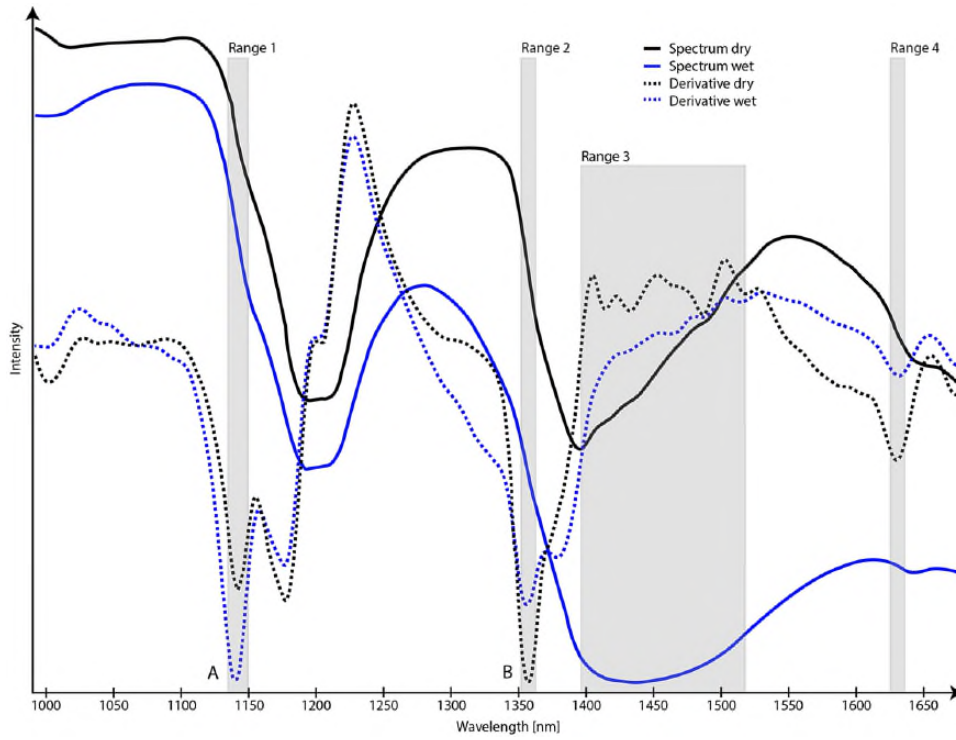


Figure 6. Comparison of raw spectrum and derivative (smoothed and normalised) of the PP spectrum with and without water influence.

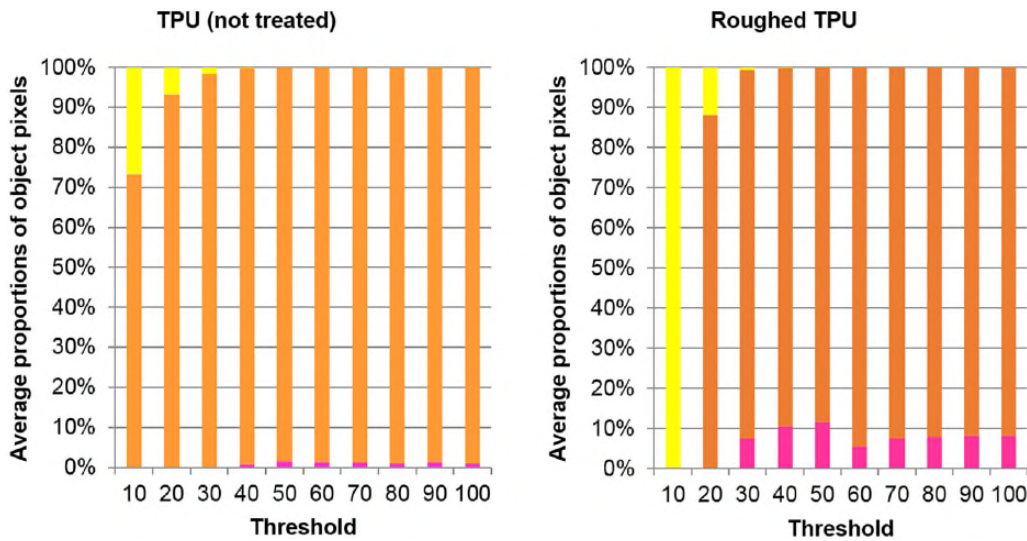


Figure 7. Average proportions of object pixels: TPU (orange), PP (pink) and unknown (yellow).

the TPU pixels, the yield dropped from approximately 96% to 71%. One explanation for this issue may be the low softening temperature of TPU; that is, the plastic fibres produced by the roughening on the object surface of the TPU particles can heat up faster and thus melt on the contact surfaces to the chute, so that higher adhesive forces between chute and TPU particles arise. This results in a non-uniform sliding speed and thus a reduced discharge of the roughened TPU particles.

Another effect of roughening the particles occurs in the distinction between LDPE_red and LDPE_white. The roughened LDPE_red particles show a slight shift in the derivative. This

change means that fewer object pixels are recognised correctly. This reduces the yield from 76.7% to 44.7%.

The improved detection of the PVC object pixels (138%) and PET particles (64%) is owing to the higher intensity of the reflected raw spectrum after roughening the surface, owing to dispersive radiation. With smooth PVC/PET particles, a distinction of the objects from the background might be problematic. Therefore, object pixels of particles with a roughened surface are rather classified as the material than as background. This effect has also been proven: In an additional experiment with a smooth PVC particle, only 2% of the reflected radiation measured as

diffusely reflected radiation. Using a roughened PVC particle, the diffuse share was 8%.

Surface moisture. The extent of the influence of surface moisture on the classification and yield depends on two factors.

1. Share of the object surface that is wetted.
2. Influence of the water layer on the reflected spectrum.

The larger the wetted surface of an object, the more object pixels can be misclassified by spectral changes. This is significantly influenced by the hydrophobic/hydrophilic properties and shape of the material. Whether this misclassification takes place, depends on how strong the influence of water is on the respective spectrum and how different the spectra of materials to be distinguished are. The average share of object pixels that is incorrectly classified can be found in Table 3.

It can be stated that most of the plastics (HDPE, PET, TPU, PVC) are partially misidentified as PP owing to the influence of water and thus classified worse overall. Exceptions are LLDPE, as well as LDPE_red and LDPE_white. As one can see in Figure 8, the effects of a moistened surface is restricted to the areas of accrued water drops. The remaining surface is correctly classified.

LLDPE was misidentified as both PP and HDPE by the influence of water. Again, the number of correctly recognised object pixels has dropped significantly. The only type of plastic whose number of correctly recognised object pixels has been improved by the water entry is LDPE_red (Table 3). It should be noted, however, that the correct recognition of the LDPE_white pixels has decreased accordingly.

Table 3. Average share of incorrectly classified pixels that can be traced back to the influence of water.

Material type	Pixel losses owing to water influence
HDPE	1.20%
LDPE_Red	-7.38%
LDPE_White	5.60%
LLDPE	2.26%
PET	10.27%
PP	0.87%
PVC	5.28%
TPU	6.66%

The yield of the investigated types of plastic has usually been reduced by the introduction of water. Exceptions are the plastics PET, LDPE_red and PVC. The improved yield of PET is owing to the shape of the test pieces. Since bent, thin-walled PET parts were used, the trials with dry material showed an average maximum yield of about 72%. This comparatively low yield is owing to uneven slippage and soaring of the particles. Wetting with water increased the particle weight of the PET objects and allowed a smoother sliding of the particles. This explains the improved yield.

The increased LDPE_red output can be explained by the higher correct classification of object pixels. The improved PVC yield owing to water entry is in contradiction to the deteriorated classification of the PVC object pixels. A possible explanation for this might be the reuse of the same particles for the experiments with dry material, while more particles had to be used for the experiments on water influence, so that a drying of the objects already used could be ensured. It can be expected that the repeated use of the dry PVC particles has led to a steady heating of the PVC parts, which promotes a more uneven sliding, explaining the reduced yield on the used chute sorter.

Implications on overall waste management

The increasing demand for recycling and the resulting ongoing propagation of sensor-based sorting machines in waste treatment and sorting plants reveal the relevance of this technology. Especially NIR technology is used to separate plastic types (Gundupalli et al. 2016), enabling, for example, material recycling and the production of refuse-derived fuels.

Common problems in such sorting steps occur in the form of false classification of plastics owing to the influence of external factors (e.g. defilements, such as surface water and roughness), resulting in potentially reduced recovery rates and quality reduction of products (Gundupalli et al., 2016). To identify such potentially problematic sorting tasks and to subsequently counteract occurring undesired effects, underlying algorithms for sorting have to be adapted.

This study provides insights into the effects of two common influencing factors (surface moisture and surface roughness) on sorting steps in waste sorting plants. By studying specific spectral



Figure 8. Misclassification of object pixels owing to water drops on TPU particles (orange): PP (pink) and unknown (yellow).

changes (in the derivatives), caused by wetting and roughening of the surface of the investigated particles, a deeper understanding of their effects with regards to application-oriented sorting algorithms can be gained. Our results show that the influence of water in obtained spectra is limited to specific wavelength ranges (1115–1680 nm or 1230–1680 nm). The given findings can be used to correctly classify defiled materials whose characteristic peaks are present in the ranges.

Furthermore, obtained knowledge may be used to indirectly improve sorting rates by changing material properties via implementing mechanical processing steps prior to sorting. Roughening of the material surface increases the amount of disperse-reflected radiation, which reduces the background noise in the derivative of the spectrum, used for the classification. By choosing the appropriate technology, for example, during shredding, a roughening of the surface can be enhanced, resulting in a raised sorting efficiency.

By following this differentiated approach for sensor-based sorting, this technology can be applied more efficiently, which improves product qualities and reduces material losses.

Conclusion and outlook

In summary, the following conclusions can be drawn from the experiments carried out.

- Higher surface roughness results in more diffusely reflected radiation, providing more raw data for processing the near-infrared spectrum.
- Increased surface roughness makes extremes in the raw spectrum more prominent, reducing signal noise in the lead, especially in the signal evaluation of clear plastic resulting in reduced spectral variation in the normalised derivative.
- The surface roughness has mostly a small influence on the classification of plastics, as long as no spectrally similar (LDPE grades or similar) or transparent material is detected and classified.
- Increased surface roughness reduces the yield of low-softening plastics on chute sorters because the sliding speed of these plastics varies as a result of the heating of the chute.
- Surface moisture causes the absorption of radiation from 1115 nm (HDPE, LLDPE, PET, PVC) or from 1230 nm (LDPE, PP, TPU) up to at least 1680 nm, which causes amplification or attenuation of various extremes in the derivative.
- Surface moisture causes at least partial smoothing of the raw spectrum, which reduces extremes in the relevant derivative of the spectrum for the evaluation.
- The influence of surface moisture on the yield of plastics is usually very low and dependent on the spectral differences between the different plastics.

By implementing the obtained information in existing or new sorting algorithms, the influence of surface water and surface

roughness could be reduced significantly or used to an advantage. The examined topics show potential for further studies to generate a deeper understanding of, for example, the role of polarisation effects and distinctive interactions of moisture or roughness and edge effects on incorrect classification. This could be especially valuable information for sorting of material with small particle sizes, showing higher proportions of edge pixels.

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References

- Blanco M and Villarroya I (2002) NIR spectroscopy: A rapid-response analytical tool. *Trends in Analytical Chemistry* 4: 240–250.
- Bünig-Pfaue H (2003) Analysis of water in food by near infrared spectroscopy. *Food Chemistry* 82: S107–115.
- Eccher-Zerbini P (2005) Emerging technologies for non-destructive quality evaluation of fruit. *Journal of Fruit and Ornamental Plant Research* 14: 12–22.
- Gschaider HJ and Huber R (2008) Neue Entwicklungen in der optischen Sortierung. *Berg- und Hüttenmännische Monatshefte* 153: 217–220.
- Gundupalli SP, Hait S and Thakur A (2016) A review on automated sorting of source-separated municipal solid waste for recycling. *Waste Management* 60: 56–74.
- Huang H, Yu H, Xu H, et al. (2008) Near infrared spectroscopy for on/in-line monitoring of quality in foods and beverages: A review. *Journal of Food Engineering* 87: S303–313.
- Maul A and Pretz T (2016) Landfill mining from the processing perspective – a view on mass balance and output streams. In: Proceedings of 3rd International Symposium on Enhanced Landfill Mining, 8–10 February 2016, Lisbon.
- Mesina MB, de Jong TPT and Dalmijn WL (2006) Automatic sorting of scrap metals with a combined electromagnetic and dual energy X-ray transmission sensor. *International Journal of Mineral Processing* 82: 222–232.
- Pretz T and Julius J (2008) Stand der Technik und Entwicklung bei der berührungslosen Sortierung von Abfällen. *Österreichischer Wasser- und Abfallwirtschaftsverband* 60: 105–112.
- Schug H, Eickenbusch H, Marscheider-Weidemann F, et al. (2007) Zukunftsmarkt Stofferkennung und -trennung; Fallstudie im Auftrag des Umweltbundesamtes im Rahmen des Forschungsprojektes Innovative Umweltpolitik in wichtigen Handlungsfeldern Available at: <https://www.umweltbundesamt.de/sites/default/files/medien/publikation/long/3456.pdf>.
- Vujić G, Jovičić N, Redžić N, et al. (2010) A fast method for the analysis of municipal solid waste in developing countries – case study of Serbia. *Environmental Engineering and Management Journal* 9(8): 1021–1029.
- Wotruba H and Harbeck H (2010) Sensor-based sorting. In: *Ullmann's Encyclopedia of Industrial Chemistry*, Wiley-VCH Verlag GmbH & Co. KGaA. DOI: 10.1002/14356007.