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Investigation of Particle Descriptors for Size Characterisation of Solid Waste Particles for Treatment Process Control

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Keywords: mixed solid waste; particle shape descriptors; particle size measurement; sensor-based measurement; process control

Abstract

Real-time control of the particle size distribution of coarsely shredded mixed solid waste has a large potential for improving the performance of mechanical processing plants. In addition to controllers and actuators, online metrology for particle size distributions is needed. In this work, 2D-images of single waste particles from the material fractions wood and plastic are investigated. The materials were gained by handsorting of shredded mixed commercial waste and the individual particles were described through different descriptors, which were used in regression models for particle size determination. It is shown that univariate models are not very likely to perform well due to the overlapping of the descriptor values for different particle size classes. Though, using a Partial Least Squares regression, that considers many different descriptors, an accuracy of over 70% was reached in most of the considered particle size classes for detecting the correct particle size in the investigated material fractions. Therefore, the potential of the method was proven, while further research is needed, to reach an accuracy level that is suitable for process control. Additionally, the evaluated particle size class must be combined with the particle weight to determine the effects of assigned particles in a particle size distribution.

Introduction

A coarse shredder is usually the first machine in mechanical treatment plants for processing mixed municipal and commercial solid waste. Together with the properties and composition of the waste input, it defines the particle sizes of the materials and therefore influences the performance of subsequent machines like screens, magnetic separators or sensor-based sorters.

To beneficially influence particle sizes in real-time – e.g. to keep them as constant as possible, independent of the input materials' variable particle size and material distribution – two components are needed in addition to a controller: controllable actuators like shredder gap width or shaft rotation speed as well as real-time-measurements of the particle size distributions. Among others, the intelligent connection of the mentioned components is part of the research within the K-project ReWaste4.0. Hence, this work aims at the metrological component, finding parameters for shape description of irregularly formed objects and implementing a real-time particle size measurement.

In general, there are different approaches for achieving this, including:

- Visual assessment from the bulk on the conveyor belt using image evaluation techniques,
- 3D-measurements of singlified particles as well as
- 2D-measurements of singlified particles.

In this contribution latter is focused by assessing the particle size class through 2D-images from single particles by a visual sensor. The software MATLAB® 2019 was used for image processing, calculation of different descriptors as well as performing univariate regressions and Partial Least Squares (PLS) regressions.

Materials and Methods

<u>Descriptors for 2D-shapes</u>

To make particle size and shape available for regression modelling, different descriptors need to be found that can be applied to particles of all shapes. Literature shows a variety of parameters to describe shapes such as equivalent diameters, major and minor axis lengths, projected area and perimeter, as well as bounding shapes [1–3].

Since coarsely shredded mixed waste shows a high irregularity in shapes and sizes, a broad range of descriptive factors was calculated from the binary images of the individual particles to empirically assess which factors deliver valuable information. These factors (later called particle descriptive factors) include the following and are presented at some exemplary particles in Figure 1**Error! Reference source not found.**:

- Projected Area: Sum of the pixels of the projected area.
- Projected Perimeter of the particle-circumscribing polygon: Due to the resolution of the images, strong unevenness (e.g. cracks, fine fringes) could be observed for all particles at the edges, which significantly influences the length of the perimeter through the selected calculation method in MATLAB®. For this reason, the perimeter of the particle-circumscribing polygon (with shrink factor = 0.5) was determined instead.
- Area equivalent circle diameter: diameter of the circle that has the same area as the projected area of the particle.
- Bounding Shapes: the smallest circumscribing rectangle (bounding box), triangle (bounding triangle) and circle (bounding circle), as well as the inner circle of the polygon (inscribed circle), are calculated and documented through their areas, radiuses and edge lengths.
- Feret diameters: describe distances between two parallel tangents, which completely enclose the particle (measuring principle of a calliper) [1–3]. To describe the size of a particle in different directions various Feret diameters are calculated including maximum and minimum Feret diameter and the respective orthogonal dimensions.
- Shape factors: To describe the shape of the particles, various dimensionless shape factors are examined. Here, the ratios between the actual particle area and the area of each bounding shape are considered. Additionally, the circularity was considered as a shape factor as well, which explains the difference of the particle from a circle. This factor was defined through equation (1) according to [4], where A_{Part} is the projected area of the particle and P_{Part} is the perimeter of the circumscribing polygon, and was defined in a way, so that it becomes 1 for a circle.

$$\text{Circularity} = \frac{4*\pi*A_{Part}}{P_{Part}^2} \qquad (1)$$

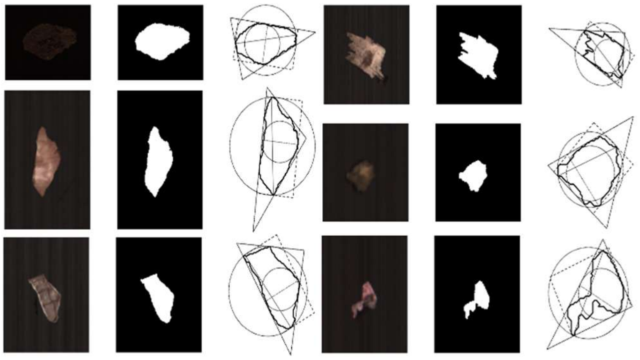

Figure 1: Examples of original RGB images, binary images and calculated 2D-descriptors (e.g. bounding shapes and Feret diameters).

Elliptic Fourier Coefficients

An additional option for describing particle shapes is the use of Elliptic Fourier Coefficients (EFC) [5]. These describe a method, where Elliptical Fourier Transformation is used to approximate the shape through overlapping ellipses, documented through a set of descriptors – four for each harmonic oscillation. This method has been successfully used for several decades to mathematically describe closed outlines.

As a starting point, the outline is described through its chain code, where each pixel of the particle outline is coded separately by assigning it a number, which gives information about its relative position to the adjacent pixels of the outline. An example is shown in Figure 2, where the particle and the way of coding are presented. The associated chain code for this example is: 0 1 1 0 0 7 6 7 6 6 5 4 4 3 4 3 3 2.

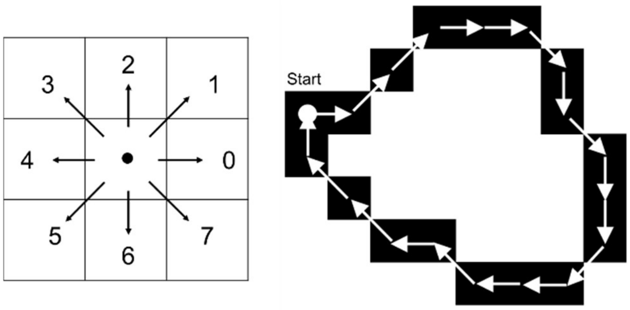

Figure 2: Coding of the different directions and illustration on an example.

Based on the chain code of a closed contour, the outline can be described using Fourier series development using ellipses. Starting with one harmonic oscillation (n = 1), the particle shape is described by an ellipse (see Figure 3), which is defined by four Elliptical Fourier Coefficients a, b, c and d. If the number of harmonic oscillations is increased, the overlap of the ellipses leads to a more detailed description of the shape. As an example, Figure 3 shows the outlines approximated by the Fourier transformation with different numbers of harmonic oscillations (n). It is shown that the accuracy of the approximation of the outline contour increases as the number of oscillations increases. In this work, the EFC up to the fifth oscillation were considered in the calculations. With a higher number of oscillations, improvements regarding the approximation of the shape to the actual particle could be found, but the changes are so small that no further benefit for describing the screening behaviour of the particles is expected.

Particularly the normalised coefficients (independent from orientation and size) of the first harmonic oscillation were examined in depth. Per definition the coefficients for that case are always classified as a=1.0, b=0.0, c=0.0, |d|<1.0 [5]. The non-zero descriptors 'a' and 'd' give the length of the semi-axis of the ellipse which describes the particle outline best. To relate the normalised coefficients with the original particle dimensions the scale factor was calculated and considered as a particle descriptive factor in the following regression model.

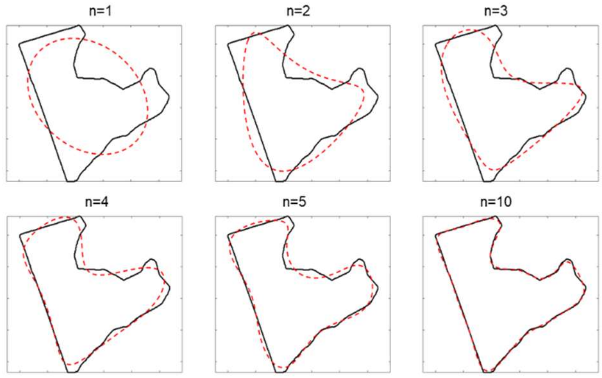

Figure 3: Visualisation of the outlines of a waste particle predicted by Elliptic Fourier Descriptors with different numbers of oscillations (n). Dashed line: approximated contour of particle-based on EFC; dotted line: original contour of particle.

Data acquisition

This work is based on results obtained from RGB photos (in png format), where each photo represents a fully shown individual particle. The particles used come from samples of coarsely shredded mixed commercial waste, that were classified by a drum screen, using the following screen cuts (in mm): 40, 60 and 80. The samples were then manually sorted and the material fractions metals (ME), plastic (3D) and wood (WO) were further processed for this work.

The fractions obtained this way were individually sent to a sensor-based sorting machine, which was able to photograph objects with a detectable NIR-signal as well as objects made of conductive metal on the moving conveyor belt using a visual sensor and to save the RGB-images of each particle. The photos were collected separately for different materials, as material classification could also be implemented online, e.g. through near-infrared sensors.

In order to achieve a better singlified input stream and separately placed objects on the conveyor belt, the material was inserted into the machine by hand. Example RGB-images that were gained this way are shown in Figure 1**Error! Reference source not found.**.

Image processing

The image files were evaluated using a code programmed in MATLAB®. The code consists of two main parts, where the first part covers the extraction of geometric dimensions and particle-describing factors, which are further processed in the second part of the program using statistical methods.

1. Extraction of geometric dimensions:

Due to the way the images were taken a distortion of the images in the direction of movement of the conveyor belt was observed and needs to be removed before calculating particle descriptive factors. The scale factor for resizing the images was conducted through an object with given dimensions and is applied to all images, which also allows evaluating the real dimensions in mm from the dimensions in pixels. Additionally, some very large particles were not fully captured on one single picture. To be sure to only consider correctly displayed images in the calculations a manual screening of all images was carried out, where incorrectly presented images were removed.

The particle descriptive factors were calculated based on the binary image. This was obtained from the RGB image via image processing (colour reversal, adjusting/utilizing brightness and contrast, converting to grayscale). Due to the image processing, small holes were detected in the binary data of the objects. In this context, holes are identified as regions indicated as background within the particle. To ignore falsely identified holes, all pixels of holes with a size smaller than 1% of the total image size were relabelled in the binary image from background to particle. Holes bigger than the chosen threshold were ignored in this step. Mechanical stressing from the sorting process of the material led to the separation of dust and fine particles, which were detected in the images. To ignore these objects in the evaluation only the biggest region of connected pixels was detected as the particle and displayed in the final binary image. With the resulting binary image, a series of size descriptive factors is calculated. Examples of original RGB images, corresponding binary images and the computed bounding shapes, as well as Feret diameters (minimum, maximum), are shown in Figure 1**Error! Reference source not found.**.

2. Regression model

Due to the high irregularity of shapes and the fact that large data sets with multiple (correlated) predictor variables were present, a Partial Least Squares (PLS)- Regression was finally used. The aim was to predict the particle size based on the particle descriptive factors and assign it to the related particle size class of the screen. Here, the following descriptive factors were used for the regression: projected particle area, perimeter of the polygon of the projected area, area of the bounding box and bounding triangle, shape factors for bounding box, bounding circle, bounding triangle, inscribed circle and circularity, minimal and maximal Feret diameter.

Results and Discussions

Overall, more than 4.500 valid images, with assigned particle size classes (in mm: 40-60, 60-80 or >80) for the material fractions wood (WO), plastic (3D) and metals (ME) were evaluated through the code. Latter presenting less than 1% of the gathered images, were not evaluated further, due to problems with image quality. The remaining fractions were investigated to find similarities and differences in the descriptive factors.

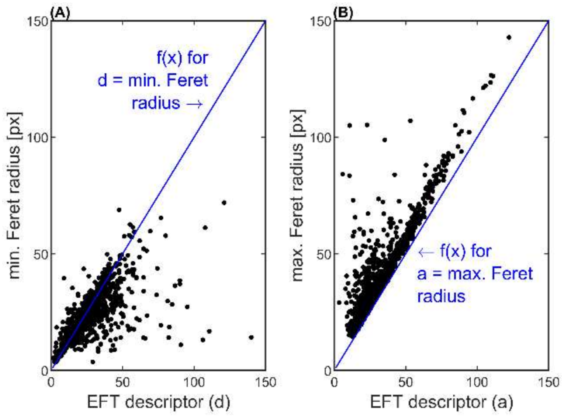

Figure 4: Visualisation of the correlations between (A) the minimum Feret radius and non-normalised EFC d (first oscillation) and (B) the maximum Feret radius and the non-normalised EFC a (first oscillation).

First, correlations between descriptors were examined, as shown in the following example: Multiplying the Fourier Coefficients ‘a’ and ‘d’ of the first harmonic oscillation by the scale factor that was calculated during the normalisation process for the Elliptic Fourier Transformation, the descriptors ‘a’ and ‘d’ can give information about the original dimensions of the particle. It turns out that they strongly correlate with half of the length of the determined Feret diameters (minimum and maximum) for both considered material classes. Figure 4 shows the relation between these variables, where the semi-Feret diameter is stated as the Feret radius. Here, the correlations between the minimum Feret radius and EFC ‘d’ (A) as well as between the maximum Feret radius and EFC ‘a’ (B) for wood particles are presented.

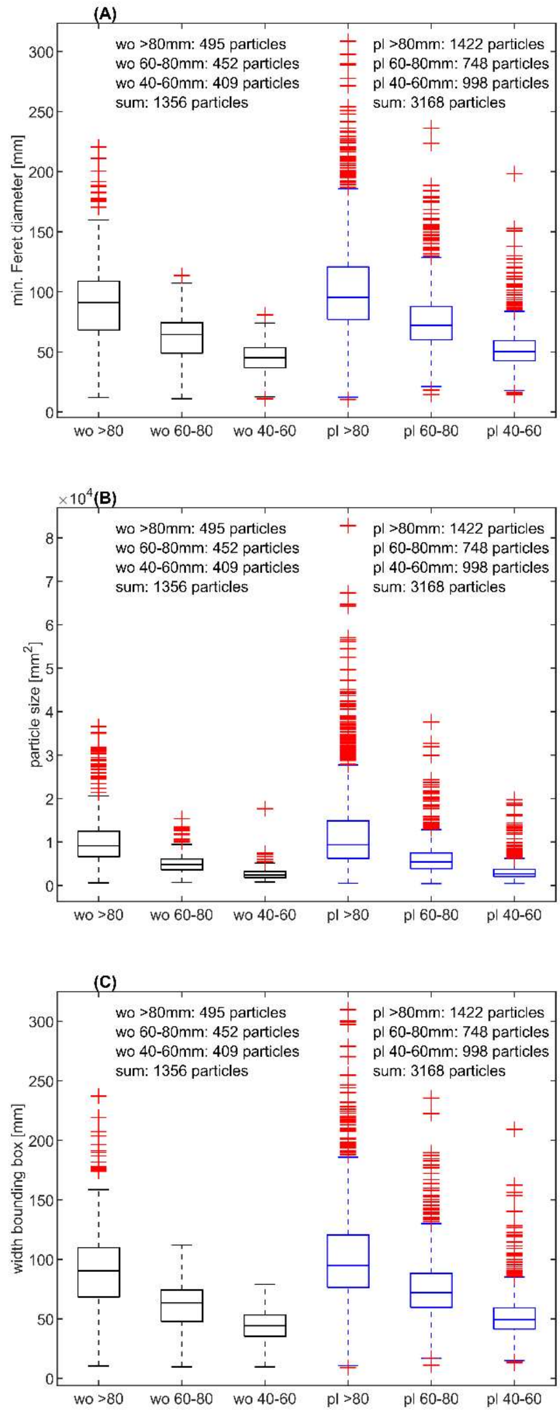

Figure 5: Visualisation of the correlation between real screen particle class size (in mm) and calculated descriptors (A)

minimal Feret diameter, (B) particle size, (C) width bounding box for the materials wood (wo) and plastic (pl).

Additionally, similar correlations can be detected between the width of the bounding box and the diameter of the inscribed circle and the minimum Feret diameter, the diameter of the bounding circle and the length of the bounding box and the maximum Feret diameter, between the diameter of the inscribed circle and the minimum Feret diameter as well as for the length of the bounding box and the maximum Feret diameter.

Subsequently, the values of the different calculated descriptors for the different particle size classes were compared, to evaluate the eligibility of the descriptors for detecting size classes. Figure 5 shows that the median of different variables (e.g. minimum Feret diameter, particle size, width of the bounding box presented on y-axis) for each screen class (x-axis) shows a trend to the assigned screen class. However, the fluctuation of the values doesn't allow a correct classification towards the real screen class. The results show as well that the material fraction plastic has a broader distribution than wood, which can be associated with the more consistent shape (flat and rectangular) of the investigated wooden particles.

In this case, the regression was performed individually for each material, while only the first four PLS components were considered as these already present most of the describable variance from the data. The results for the materials wood and plastic are presented in Table 1. To compare measurements with different units the data sets were normalized in a way that each variable had a mean of zero and a standard deviation of 1. To properly evaluate the models the data was split into two separate groups, one containing 80% of the data from each particle size class, which was randomly picked. This data is later called the calibration data. The remaining data is used to test the quality of the developed model and is therefore called test data.

Furthermore, the quality of the regression models is described by counting the particles which were assigned to the right and wrong particle size classes based on the PLS-results. The results are presented as a mean from 15 individual tests. Here, the test samples consisted of 100 randomly picked particles for each particle size class (total of 300 particles per sample) that were virtually put together from the created test data sets for each material fraction.

Table 1: Detailed mean results from the applied regression models of 15 randomly arranged data sets consisting of 300 particles (100 in each particle size class) for the materials wood and plastic (values in %).

	classified to particle size 40-60mm	classified to particle size 60-80mm	classified to particle size >80mm
	Material: wood		
real particle size 40-60mm	**78**	21	1
real particle size 60-80mm	23	**50**	27
real particle size >80mm	8	16	**76**
	Material: plastic		
real particle size 40-60mm	**77**	18	5
real particle size 60-80mm	23	**45**	32
real particle size >80mm	9	19	**72**

The samples composition based on the predicted particle sizes were then evaluated with the PLS-regression model, reaching a mean total accuracy of 68.0% for wood and 64.7% for plastics. Table 1 shows the mean results over the fifteen test samples, where information about correctly and falsely classified particles for each particle size class is given individually. Here, in all investigated particle size classes the majority of the particles was classified correctly. Overall the number of correctly classified object was slightly higher for wood than for the plastic fraction, which can be explained by the more uniform wooden objects (more rectangular) in the samples while the plastic particles showed more irregularity in the shapes.

The results show the potential of the method, while there are still challenges to be faced. On one hand, for some materials (in this case metals) the image quality is not sufficient, mainly due to the darkness of the images, so that they could not be distinguished from the background. Large plastic objects were often cropped and not fully displayed on the images, which made them not useable in the regression.

For the recording of images by the RGB sensor of the sensor-based sorting machine a detected NIR-signal was crucial. This factor mainly caused dark (especially black and grey) objects to not be considered in the evaluation. Additionally, certainly shaped objects (one-dimensional) were recorded on multiple separate images and therefore not useable in the investigation.

Therefore, suitable imaging methods need to be developed, while considering the harsh conditions on a conveyor belt in a real waste treatment plant.

Conclusions

This work gathers several descriptors for particle size and shape. It also shows correlations between many of these, so that some information is redundant when calculating all of them. Therefore, the application of feature reduction methods, such as PLS is obvious.

It is shown for some descriptors, such as the minimum Feret diameter, that univariate regression models will hardly be able to detect screen particle size classes, due to scattering and therefore overlapping of the descriptors' values for the different size classes. Though, when using a PLS model, considering multiple descriptors, an accuracy of 68.0% in total is reached for wood. This reached accuracy is likely not to be sufficient for advantageous process control. Thus, further research is needed, to improve the classification quality of the model. This research might include the creation of a data set with narrower particle size classes, as well as using higher-order models or additional descriptors. Furthermore, classification through machine learning algorithms, as well as 3D-imaging should be examined. If the effects on a particle size distribution should be investigated, the partly compensating effect between falsely classified particles must be considered which might lead to a more correct representation of the material distribution in respective particle size classes.

Finally, the method still requires signification of the material, which will not be possible at every interesting point in a plant. But it could provide a first automated method for measuring the particle size distribution for mixed solid waste, that can be used for material analysis, as well as for the creation of the huge datasets that will most likely be necessary for visual particle size distribution assessment from the bulk.

Extended research regarding this topic was already performed. The results are currently under review and are going to be published in a peer-reviewed journal under the title "Sensor-based particle size determination of shredded mixed commercial waste based on two-dimensional images" [6].

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References

[1] E. Olson, "Particle Shape Factors and Their Use in Image Analysis–Part 1: Theory," *Journal of GXP Compliance*, 15-3, pp. 85–96, 2011.
[2] G. Dunnu, T. Hilber, and U. Schnell, "Advanced Size Measurements and Aerodynamic Classification of Solid Recovered Fuel Particles," *Energy Fuels*, vol. 20, no. 4, pp. 1685–1690, 2006, doi: 10.1021/ef0600457.
[3] F. Podczeck, "A shape factor to assess the shape of particles using image analysis," *Powder Technology*, vol. 93, no. 1, pp. 47–53, 1997, doi: 10.1016/S0032-5910(97)03257-9.
[4] M. L. Hentschel and N. W. Page, "Selection of Descriptors for Particle Shape Characterization," *Part. Part. Syst. Charact.*, vol. 20, no. 1, pp. 25–38, 2003, doi: 10.1002/ppsc.200390002.
[5] F. P. Kuhl and C. R. Giardina, "Elliptic Fourier features of a closed contour," *Computer Graphics and Image Processing*, vol. 18, no. 3, pp. 236–258, 1982, doi: 10.1016/0146-664X(82)90034-X.
[6] L. Kandlbauer, K. Khodier, D. Ninevski, and R. Sarc, "Sensor-based Particle Size Determination of Shredded Mixed Commercial Waste based on two-dimensional Images", 2020 (Status September 2020: Under Review).