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Motion-based material characterization in sensor-based sorting

Bewegungsbasierte Charakterisierung von Materialien für die sensorgestützte Sortierung

Abstract: Sensor-based sorting provides state-of-the-art solutions for sorting cohesive, granular materials. Typically, involved sensors, illumination, implementation of data analysis and other components are designed and chosen according to the sorting task at hand. A common property of conventional systems is the utilization of scanning sensors. However, the usage of area-scan cameras has recently been proposed. When observing objects at multiple time points, the corresponding paths can be reconstructed by using multiobject tracking. This in turn allows to accurately estimate the point in time and position at which any object will reach the separation stage of the optical sorter and hence contributes to decreasing the error in physical separation. In this paper, it is proposed to further exploit motion information for The purpose of material characterization. By deriving suitable features from the motion information, we show that high classification performance is obtained for an exemplary classification task. The approach therefore contributes towards decreasing the detection error of sorting systems.

Keywords: Optical inspection, sensor-based sorting, multiobject tracking, classification.

Zusammenfassung: Für die Sortierung von kohäsiven, granularen Materialien entspricht die sensorgestützte Sortierung dem Stand der Technik. Die Auswahl geeigneter Systemkomponenten, wie etwa Sensorik, Beleuchtung, oder die Realisierung der Datenauswertung, orientiert sich bei der Entwicklung entsprechender Systeme an der konkreten Sortieraufgabe, die es zu lösen gilt. Eine Gemeinsamkeit findet sich im Einsatz scannender Sensoren. Jüngst wurde jedoch der Einsatz von Flächenkameras vorgeschlagen. Durch die Beobachtung von Objekten zu mehreren Zeitpunkten besteht die Möglichkeit, deren Bewegungspfade zu verfolgen. Dies erlaubt eine präzise Schätzung der Position und des Zeitpunkts, zu welchem ein Objekt die Trennstufe des Systems erreicht und hilft somit dabei, den Fehler in der physikalischen Separation zu verringern. In dieser Veröffentlichung wird vorgeschlagen, diese Bewegungsinformation ebenfalls zur Charakterisierung von Materialien zu verwenden. Durch die Ableitung geeigneter Merkmale zeigen wir exemplarisch für eine Klassifikationsaufgabe, dass hierdurch gute Ergebnisse erzielt werden können. Der vorgestellte Ansatz trägt damit zur Verringerung des Erkennungsfehlers in Sortiersystemen bei.

Schlüsselwörter: Sichtprüfung, sensorgestützte Sortierung, Multiobjekt-Tracking, Klassifikation.

1 Introduction

Sensor-based sorting has found wide application in industrial contexts, including food processing [1], waste management [2], as well as sorting of industrial materials like, for instance, minerals and metals [3]. It offers solutions for sorting cohesive, granular materials on a large scale.

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A typical setup of such a sorting system consists of a conveyor belt, line-scan cameras operating in the visible spectrum, and compressed air nozzles. In the case of an *accept or reject task*, low-quality or potentially dangerous entities need to be removed from the feed. When an object falls into the *reject class* of a binary sorting task, it has to be removed from the feed, which is done by activating corresponding compressed air nozzles. This leads to a deflection of the object and therefore realizes the physical separation. However, heterogeneous material feeds, especially ones containing granular components, are inherently difficult to sort into different classes.

Sensor-based sorting combines techniques from several different disciplines, like mechanical process engineering, machine learning, sensor technology, and computer vision. In terms of machine learning, sensor-based sorting can be formulated as a multinomial classification task with the addition that each class also has to be physically separated from one another. In the case of conventional systems, perfect flow control is desired, which means that the material moves with a defined, constant velocity, such that the exact time the object reaches the array of air nozzles can be predicted reliably. For conventional systems, this is crucial in order to minimize the error in physical separation, since after passing the line-scan camera, no further information can be obtained in order to localize the object at the point of separation. Consider, for instance, a material feed consisting of valuable minerals and some other non-valuable bulk material. Falsely rejecting objects should then be minimized. Achieving perfect flow control is a hard task for certain materials. This is primarily due to interactions and irregular movement of objects on the conveyor belt. In the feeding phase, materials are accelerated and they eventually reach the velocity of the conveyor belt. However, depending on the geometry and mass of the objects, motion characteristics could differ. In order to achieve better results, it has been proposed to replace line-scan cameras by area-scan cameras [4].

This paper extends the work presented in [5]. We show that tracking information can be utilized to increase characterization performance. Velocity and acceleration of an object are derived by applying multiobject tracking to a series of images. By using integral features like the velocity, certain objects can be distinguished from one another without utilizing optical properties like the color. It is important to note that the proposed approach also allows extracting features as utilized in state-of-the-art optical sorting systems. Our results suggest that classification performance for certain products can be increased significantly by exploiting the additionally available information about objects.

2 Related work

There is a large variety of sensor-based sorting systems. Design choices depend on the kind of material to be sorted. Such choices include the selection of appropriate sensors [6] and possibly illumination [7]. Modern systems use line-scan cameras together with some sort of transport mechanism, e.g. a conveyor belt. Automated sorters are either used stand-alone, or they are embedded in a more complex sorting process where material feeds go through a pipeline of different sorting systems [2]. The separation efficiency is affected by many factors, including material size, sensitivity and accuracy of the sensors, and the classification performance. A high throughput is necessary to make large-scale industrial sorting feasible. However, an increase in throughput decreases the separation efficiency and research has been carried out in order to predict performance as a function of throughput [8, 9].

The image processing pipeline in optical sorting includes segmentation of the image data, detecting regions containing objects, and classification of those [10]. For the latter, color related properties are often used [11]. Recently, it has been proposed to use area-scan cameras instead of line-scan cameras [12]. Objects are observed at multiple time points and trajectories can be derived [4]. Those trajectories can be used in order to decrease the error in physical separation by extrapolating the point in time and the position when an object reaches the separation stage [13].

3 Method

In order to obtain data that can be used for characterization of objects based on their movement, it is required that each individual object is observed by the camera multiple times, which is not the case for conventional systems using line-scan cameras. When using an area-scan camera with a sufficiently high frame rate instead, observations for several time points are available. However, each frame contains multiple objects, possibly several thousand. Therefore, the correspondences between objects in successive frames need to be determined in order to reconstruct their path. This can be achieved by applying multiobject tracking which is further discussed in Section 3.1. A description of the system that was used to acquire data used for experimentation is provided in Section 3.2. Once all required information is available, features can be derived based on the resulting tracks, which is subject to discussion in Section 3.3.

3.1 Multiobject tracking in sensor-based sorting

The goal of multiobject tracking in this context is to combine information about each individual object in successive frames into a track, see Figure 1. Typically, the image data received from the sensor is pre-processed in the first step during data analysis. Following that, regions actually containing objects need to be identified. For these regions, the position of objects, e.g. the centroid of the 2D projection, can be determined. For each obtained frame, these measurements serve as the input for the multiobject tracking algorithm.

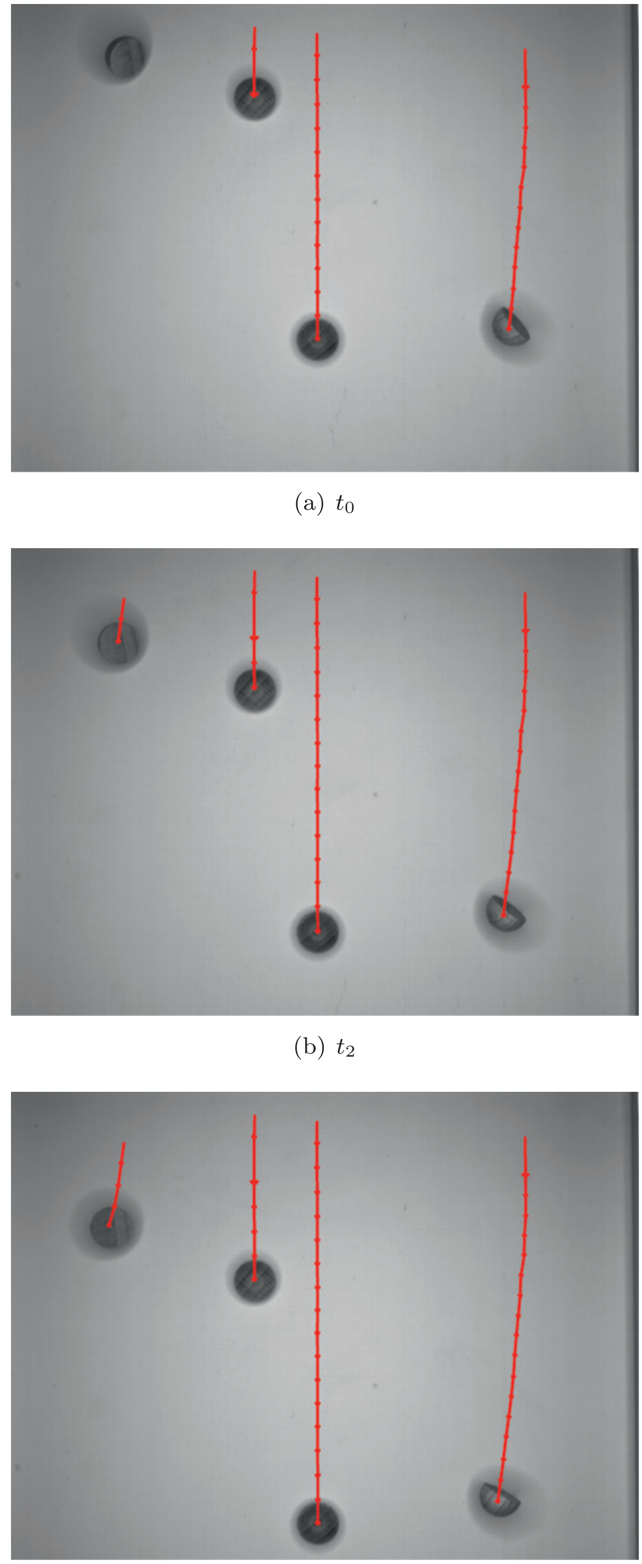
Utilizing the assignments between a measurement and a track, a standard Kalman filter is used for the purpose of state estimation. The 2D position as well as velocity for both direction components serve as state variables. In order to associate the predictions for the existing tracks to the measurements in each frame, an algorithm solving the Linear Assignment Problem, which is formulated as minimizing

$$\begin{aligned} & \sum_{i=1}^{N}\sum_{j=1}^{M} a_{i,j}x_{i,j} \\ \text{s.t.} \quad & \sum_{j=1}^{M} x_{i,j} = 1 \quad \forall i = 1,\dots,N\,, \\ & \sum_{i=1}^{N} x_{i,j} = 1 \quad \forall j = 1,\dots,M \end{aligned} \tag{1}$$

is utilized. Here, N and M denote the sets of predictions and measurements, respectively. Furthermore, $x_{i,j} = 1$ whenever prediction i is assigned to measurement j and $x_{i,j} = 0$ otherwise. The cost of assigning prediction i to measurement j is given by $a_{i,j}$ and depends on a distance function. Further information about the system is also provided in [4, 12] and the challenge of tackling real-time requirements for sensor-based sorting is discussed in [14]. As the result of the multiobject tracking, the path of each individual object and the measurements with the corresponding frame numbers integrated in the path are known. However, it is important to note that those lists may vary in length due to different numbers of observation time points for the objects.

3.2 Experimental setup and data acquisition

In order to acquire data that can be used for motion-based classification an experimental setup was implemented. As a sensor-based sorting system, a miniature version of an



(a) t_0

(b) t_2

(c) t_4

Figure 1: Illustration of consecutive frames and the track of each contained object. Transport direction is top to bottom.

optical belt sorter, as also simulated in [15], was used. While the system is smaller in size compared with industrial settings, it consists of a comparable hardware setup. For instance, objects are fed into the system using a vibrating feeder. From there, they pass down a slide onto a conveyor belt. Setting up the system according to the conventional design, the material is observed right after falling off the belt by a line-scan camera and potentially deflected by one or several compressed air nozzles. However, in the course of this work, image data was acquired while the material was transported on the belt using an area-scan camera of the type *Bonito CL-400* running at approximately 192 Hz.

The conveyor belt has a total length of 60 cm and is schematically illustrated in Figure 2. For all conducted experiments, it was configured to run at 1.1 ms^{-1}. The characteristic of the motion of objects is strongly influenced by the length of the belt. Generally, the longer an object is transported on the belt, the more equal becomes its velocity to the one of the belt. The degree to which objects adopt to the transport velocity of the conveyor belt is also denoted as flow control. In order to observe the material at different degrees of adaption, different belt lengths are considered. This is realized by mounting the camera at different positions along the belt at a fixed distance, see Figure 2. The area denoted as *feeding* is located right after objects enter the belt and covers the first ~ 11 cm. The area ranging from ~ 23 cm to ~ 34 cm is referred to as *center*. Lastly, the area *edge* covers the last ~ 8 cm of the belt before the material falls off.

The chosen classification task aims at discriminating 4 sphere-like products as illustrated in Figure 3 for which similar, yet unequal motion characteristics are expected. The objects of all classes, i.e. wooden hemispheres, wooden spheres, wax beads, and cotton balls, have a diameter of 10 mm and differ in terms of surface friction and weight.

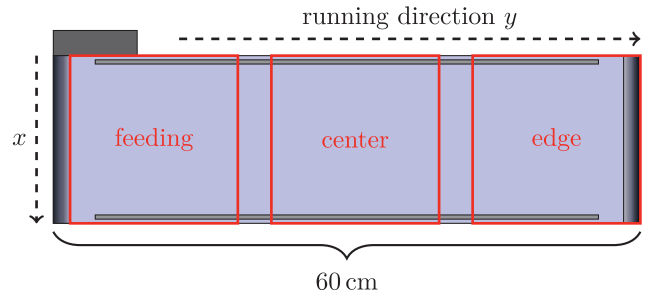
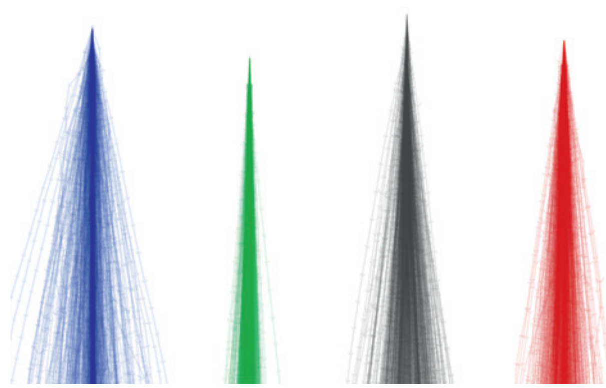


Figure 2: Schematic illustration of the conveyor belt as viewed from above and the considered areas for image acquisition.

(a) Wooden hemi-spheres, ~0.26 g (b) Wooden spheres, ~0.4 g (c) Wax beads with a hole, ~0.47 g (d) Cotton balls with a hole, ~0.24 g

Figure 3: Products used for experiments.



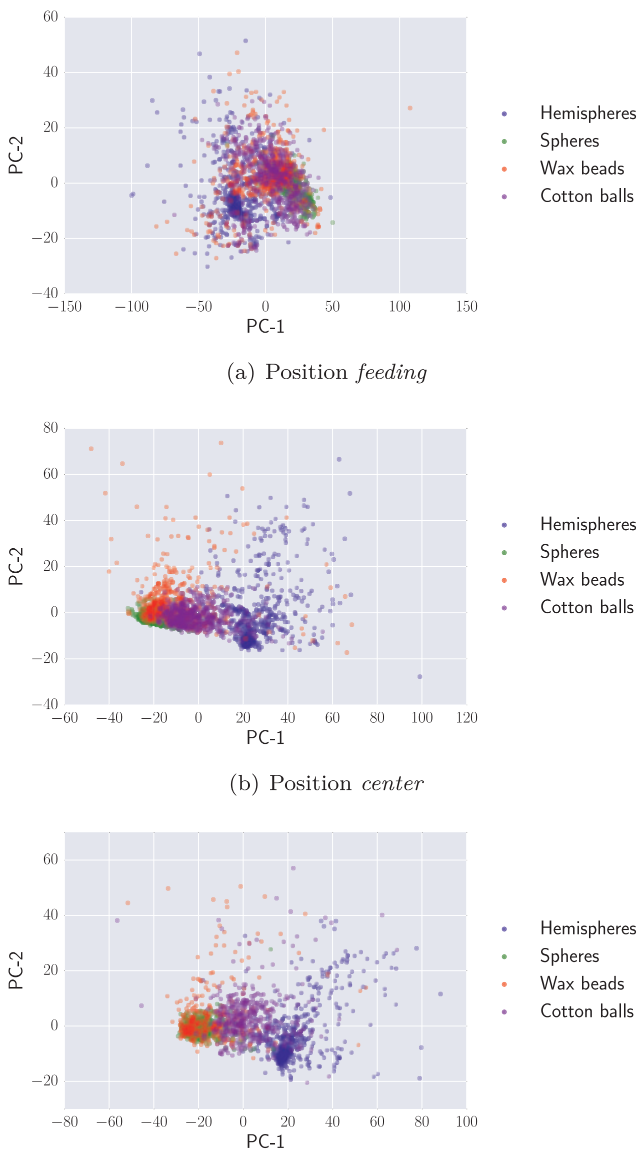
(a) Hemispheres (b) Spheres (c) Cotton balls (d) Wax beads

Figure 4: Tracks aligned at the same origin for data-sets recorded for the area *center*. Transport direction is top to bottom.

3.3 Motion-based features

The image data acquired according to the description provided in Section 3.2 is processed offline in several steps. First, an average background image is calculated for the purpose of segmentation. By subtracting the average background from each other frame and applying blurring, regions containing objects are identified and the midpoints of the 2D projection are calculated. Therefor, for each dataset, a list of measurements described by the frame number as well as the x and y position (see Figure 2) is generated. This information serves as the input for the multiobject tracking system as discussed in Section 3.1. This processing step allows us to assign each new measurement to a track.

The origin of each track depends on the distribution of objects from feeding and may be assumed to be random. Translating all tracks to the same origin corresponds to normalizing the data. Expressive features like velocity or acceleration are translation invariant. By aligning all tracks, it is possible to gain more insight into the motion characteristics and especially it is easier to see the spatial distribution differences of the tracks. The result is exemplary visualized for the different products for area *center* in Figure 4. As can be seen, independent of the



(a) Position *feeding*

(b) Position *center*

(c) Position *edge*

Figure 5: Visualisation of the first and second component resulting from PCA for the different observation areas.

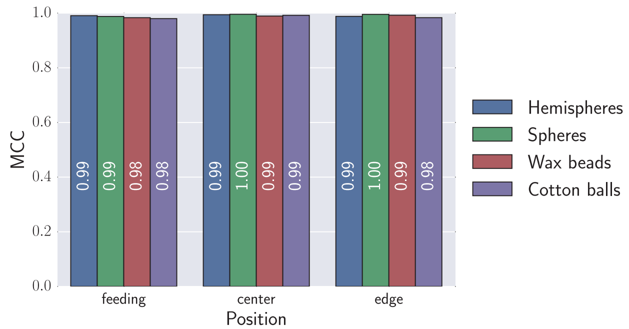
product, mainly motion in transport direction exists. However, products differ in terms of motion perpendicular to transport direction. For instance, for hemispheres, much more motion perpendicular to transport direction compared with spheres can be observed, while for cotton balls and wax beads the paths appear rather similar.

In order to prepare the data for the classification task, features need to be extracted. Motivated by the observations stated above, integral features, i.e. features based on information from multiple time points, based on velocity and acceleration, were chosen. Features representing the actual path of the objects, such as coefficients of a fitted polynomial, were not respected. We further categorize features to be either global or local, whereas a global feature refers to information obtained for the entire observation sequence of an object and local features are based on 2 successive measurements for velocity related features and 3 for acceleration related features. The final feature vector is of dimensionality 14 and contains the number of measurements obtained, the global velocity of the object, the local minimal, average, and maximum velocity individually for the x and y component as well as the local minimal, average, and maximum acceleration individually for the x and y component.

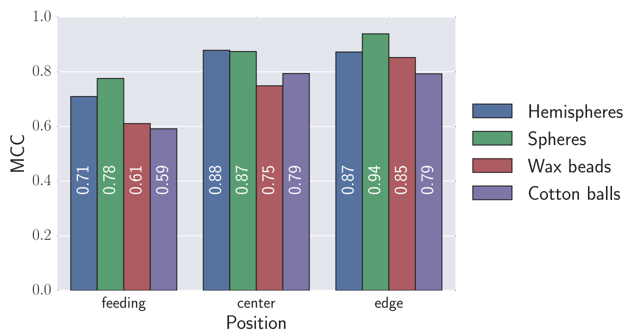
In order to validate the typically error-prone process of manual feature selection, Principal Component Analysis (PCA) is performed on the data. The resulting first and second components for the different observation areas are illustrated in Figure 5. As can be seen, for the position *feeding*, clusters can be observed although a strong overlap between the different classes exist. However, for the positions *center* and *edge*, the overlap and also the number of outliers decreases and clusters form even more compact.

4 Evaluation

The success of the method is demonstrated by training a random forest classifier consisting of 10 estimators on the data. Matthews correlation coefficient (MCC) [16] is used as a measure of quality. In order to estimate an upper bound of performance, the entire data was used both for training and testing. The results are provided in Figure 6 (a). As can be seen, for each observation areas and all classes, excellent values ranging between 0.98 and 1.0 are obtained. Therefore, it is concluded that the data indeed is suitable for discrimination of the different classes. An example of the resulting classification performance when splitting the data into a training and testing subset is shown in Figure 6 (b). In this scenario, $^2/_3$ of the data was used for training. The random splitting was performed multiple times and the provided results are representative. From Figure 6 (b) it can be seen that, in general, wooden spheres and hemispheres can be detected most accurately for all observation areas. It can also be concluded that classification performance increases with the length of the belt used for transportation, i.e. from position *feeding* over *center* to *edge*. A possible explanation for this can be that the degree of adaption to transportation velocity reveals most insightful motion properties. If this was indeed the case, it would be clear that performance would drop dramatically once the belt length is sufficiently long such that all objects have perfectly adapted to transportation velocity and



(a) Same training and test data



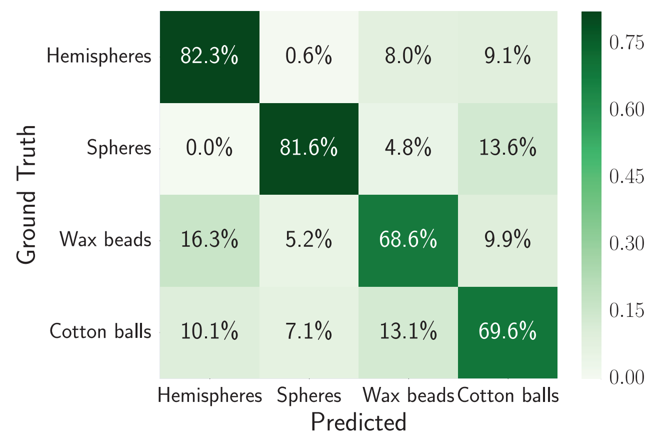
(b) Random data split for training and testing (test size = 1/3)

Figure 6: Random forest classifier performance.

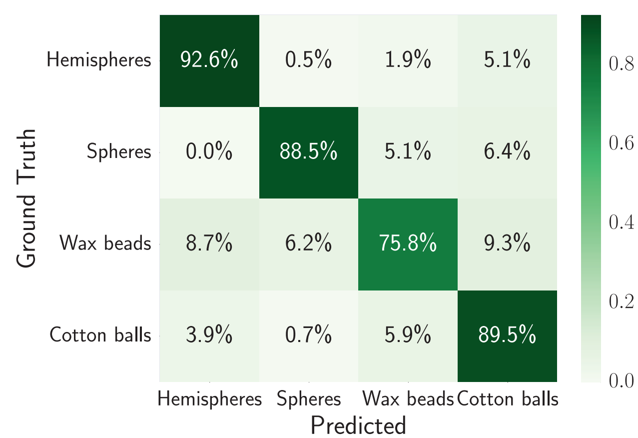
hence would not differ with respect to their motion behavior. Also, it might be the case that at position *feeding*, the motion of objects is rather random. However, this is to be confirmed by further experimentation.

From the confusion matrices provided in Figure 7, errors made during classification can be identified. It can be observed that certain errors seem to disappear with increased belt length, such as spheres falsely identified as cotton balls and hemispheres identified as wax beads. However, certain types of errors also increase from *center* to *edge*, such as cotton balls falsely held for hemispheres.

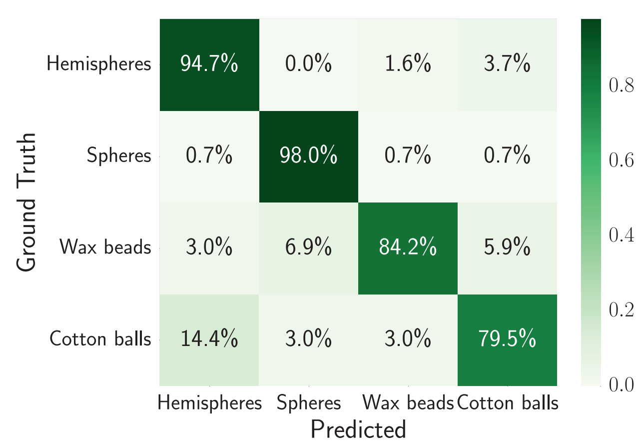
More insights regarding the importance of features as described in Section 3.3 are provided in Figure 8. Here, the Gini importance [17] is used to rank the features according to their importance to the classification task. As can be seen, for all observation areas, velocity related features are of highest importance. It also is noteworthy that with respect to velocity, mainly v_y, which denotes velocity in transport direction, is of importance, whereas with respect to acceleration the axis aligned perpendicular to transport direction is of highest importance. Also, it can clearly be seen that the dominance of single features seems to increase over the time spent on the conveyor, i.e. from position *feeding* over *center* to *edge*.



(a) Position *feeding*

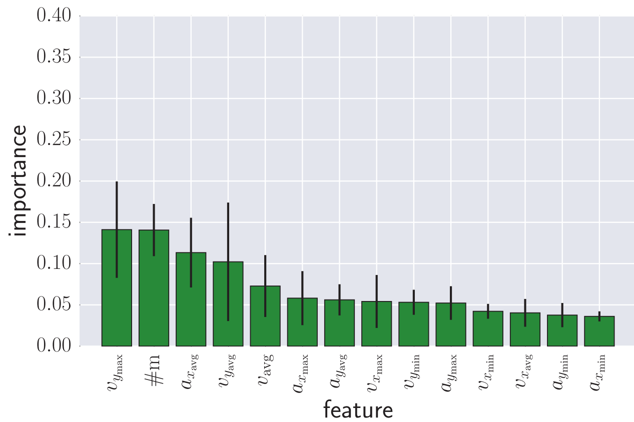


(b) Position *center*

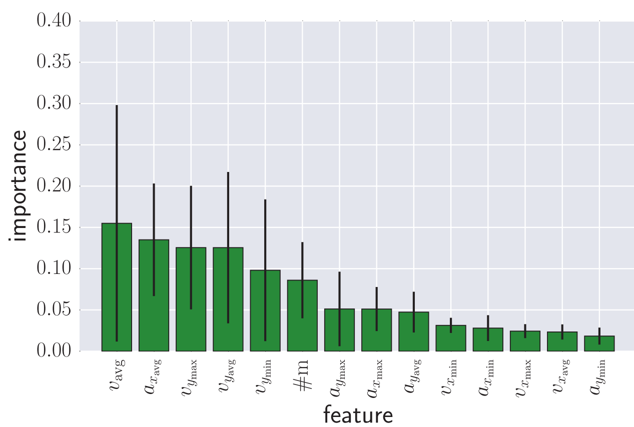


(c) Position *edge*

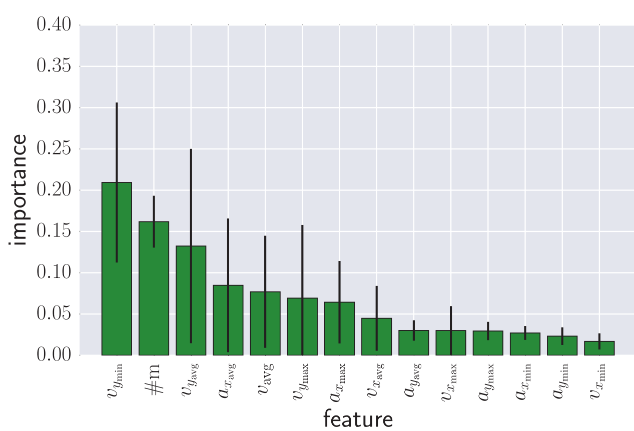
Figure 7: Normalized confusion matrices when splitting data for training and testing.



(a) Position *feeding*



(b) Position *center*



(c) Position *edge*

Figure 8: Illustration of the Gini importance for the different positions. The error bars indicate the inter-trees variability.

From the presented results, it can be concluded that motion-based features are expressive characteristics that allow or increase performance for discrimination of products. While the classification task presented in this paper was solely based on motion-based features, it is assumed that a combination with features traditionally used in sensor-based sorting, such as color-based and geometric, can lead to high classification performance and hence minimize the error in characterization of materials.

5 Conclusion

In this paper, it was shown how multiobject tracking in sensor-based sorting can not only decrease the error in physical separation but also in material characterization. This was demonstrated by utilizing motion-based features for discriminating certain products. An experimental setup was presented that allows acquiring required image data and a set of features describing the motion of an object was derived. Furthermore, results were presented for three different virtual belt lengths by mounting the camera at three different positions and hence different degrees of flow control. While promising results were obtained for all configurations, results indicate that the difference in adaption to the transport velocity reveals the most insightful properties.

In the future, we intend to pursue purely data-driven approaches, which avoid the error-prone step of manual feature selection. However, corresponding methods typically require a huge amount of training data to be available. For this purpose, the experimental setup needs to be extended in a way that allows collecting the required amount of data in a feasible manner. Moreover, the behaviour of colliding objects might reveal interesting features useful for characterization. Also of particular interest are scenarios that require both optical and motion-based information in order to discriminate materials. Furthermore, for application in an industrial setting, challenges such as respecting real-time requirements need to be taken into consideration. Lastly, considerations regarding system design need to be made. For instance, instead of aiming at perfect flow control, it might be beneficial to use setups which support revelation of object characteristics by not suppressing their motion characteristics. Yet, this requires precise predictions for physical separation.

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