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Improving material characterization in sensor-based sorting by utilizing motion information

Georg Maier[1], Florian Pfaff[2], Florian Becker[1], Christoph Pieper[3], Robin Gruna[1], Benjamin Noack[2], Harald Kruggel-Emden[3], Thomas Längle[1], Uwe D. Hanebeck[2], Siegmar Wirtz[3], Viktor Scherer[3] and Jürgen Beyerer[1]

[1] Fraunhofer Institute of Optronics, System Technologies and Image Exploitation IOSB
Fraunhoferstr. 1, 76131 Karlsruhe, Germany
[2] Karlsruhe Institute of Technology,
Intelligent Sensor-Actuator-Systems Laboratory
Adenauerring 2, 76131 Karlsruhe, Germany
[3] Ruhr-Universität Bochum, Department of Energy Plant Technology
Universitätsstraße 150, 44780 Bochum, Germany

Abstract Sensor-based sorting provides state-of-the-art solutions for sorting of cohesive, granular materials. Systems are tailored to a task at hand, for instance by means of sensors and implementation of data analysis. Conventional systems utilize scanning sensors which do not allow for extraction of motion-related information of objects contained in a material feed. Recently, usage of area-scan cameras to overcome this disadvantage has been proposed. Multitarget tracking can then be used in order to accurately estimate the point in time and position at which any object will reach the separation stage. In this paper, utilizing motion information of objects which can be retrieved from multitarget tracking for the purpose of classification is proposed. Results show that corresponding features can significantly increase classification performance and eventually decrease the detection error of a sorting system.

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

1 Introduction

Sensor-based sorting technology enables the separation of a material feed into different classes. Typically, systems are used to remove low-quality or potentially dangerous entities from a feed. Applications are found in food processing [1], waste management [2], as well as sorting of industrial minerals [3]. The sorting process is commonly subdivided into the stages feeding, presentation, data analysis, and physical separation. Systems further differ in regard to the applied transport mechanism, sensors, and separation mechanism. A widespread setup regarding these components consists of a conveyor belt, line-scan cameras operating in the visible spectrum, and compressed air nozzles. Whenever an object is to be removed from the feed, it is deflected during a flight phase by activating corresponding nozzles. Hence, errors in sorting occur whenever an object to be accepted is falsely deflected and contrariwise. Which of these two errors is of higher importance depends on the sorting task at hand. However, both result from various errors that may occur, such as sensor errors, detection errors, or errors in physical separation.

For conventional systems utilizing scanning sensors, it is desired to achieve perfect flow control, i.e. the material moves with a defined, constant velocity. This is due to a delay between presentation and physical separation. Between these two points in time, no further information about an object can be obtained. Therefore, all objects are required to reach an expected velocity in order to be able to reliably predict the point in time as well as the position when the particles reach the array of air nozzles and hence minimize the error in physical separation. For certain products, this is a very hard task. In order to be able to also sort products for which perfect flow control is infeasible to achieve, replacing line-scan sensors by area-scan sensors has recently been proposed [4]. A sufficiently high frame-rate provided, objects can be observed at multiple points in time. By applying multi-target tracking, the velocity of the object can be determined. This way imperfection in flow control can be compensated and potential errors in physical separation can be reduced.

In this paper, it is demonstrated that information derived from tracking of the objects can also increase detection performance. More precisely, integral features such as the velocity are derived from the tracks.

These features can then be used to characterize objects contained in the feed. Therefore, classification can be performed on the basis of physical motion behavior and hence non-optical properties. To our best knowledge, this is the first time such an approach has been proposed for sensor-based sorting. Results show the approach can significantly increase classification performance for certain products.

2 Related work

Sensor-based sorting is a field of growing importance with widespread applicability. Corresponding systems can be used stand-alone, e.g. to clean a feed from impurities, or as a step of more complex sorting processes [2]. In many cases, systems are tailored to a specific task at hand and hence exploit knowledge about the material to be processed. This includes the selection of appropriate sensors [5] and possibly illumination [6]. State of the art systems employ scanning sensors such as line-scan cameras. Consequently, the material is required to be in motion, which is achieved by a corresponding transport mechanism. For instance, systems include a conveyor belt or the material is running down a slide or chutes. Derivation of the sorting decision, which typically can be regarded as an *accept or reject* task, is performed via data analysis. For cohesive, granular materials, arrays of compressed air nozzles are used for the task of physical separation. In optical sorting, sensor data can be interpreted as an image, hence image processing is performed. This includes segmentation of the image data, detecting regions containing objects, and classification of those [7]. For the latter, color related properties are often used [8].

Recently, replacing line-scan sensors by area-scan sensors has been proposed [9]. By obtaining sensor data for multiple points in time for each object contained in the feed, multitarget tracking can be utilized to gain insight into the trajectory of an object [4]. This eventually allows decreasing the error in physical separation since more accurate assumptions regarding the point in time as well as the position when an object reaches the separation stage can be employed. This paper extends these works by also utilizing motion information for the discrimination of objects.

3 Motion-based discrimination of products

The proposed approach aims at increasing detection performance by incorporating motion-related characteristics of individual objects of the feed. In the following, the methodology for deriving such features as well as the evaluation setup considered in this paper are presented.

3.1 Methods

In sensor-based sorting, the main direction in which objects are moving is defined by the system setup. For instance, using a conveyor belt, objects mainly move with the running direction of the belt. In order to obtain data that can be used for characterisation of objects based on their movement, it is required that each individual object is observed by the camera multiple times. Considering an area-scan sensor, this can be achieved by a sufficiently high frame rate.

From the image data, the position of objects, e.g. the centroid of the 2D projection, can be determined. This results in a set of points for each obtained frame. By applying multitarget tracking, information about the same object in successive frames can be combined into a track. Briefly, a standard Kalman filter is used for state estimation including the 2D position as well as velocity for both direction components as state variables. Also, an algorithm solving the Linear Assignment Problem is used for the association between retrieved measurements and existing tracks. A detailed description of the system is provided in [4,9]. Eventually, the path of each individual object can hence be described by a list of centroid measurements. However, these may vary in length due to different number of observation time points for the objects.

In the course of this work, basic motion-related key figures based on velocity and acceleration are manually selected. With respect to velocity, one temporally global as well as several temporally local features are considered. In this context, a global feature refers to information obtained for the entire observation sequence of an object. Local features are based upon 2 successive measurements for velocity related features and 3 for acceleration related features. The final feature vector is of dimensionality 14 and is a composite of the following numerical values:

- 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.
- The local minimal, average, and maximum acceleration individually for the x and y component.

It should be noted that local features, which are in the majority, can be computed in-line to the observations, while global features require identifying that an object left the observable area.

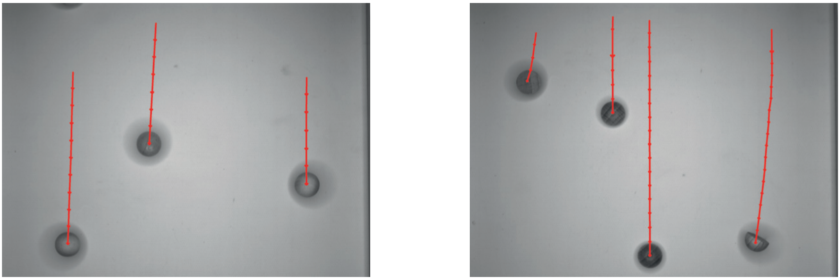
3.2 Evaluation framework

The described approach was validated experimentally. For this purpose, 4 products were identified for which similar, yet not equal motion characteristics may be expected. An illustration of the products is provided in Figure 11.1 (l.t.r): wooden hemispheres, wooden spheres, wax beads, and cotton balls. All objects have a diameter of 10 mm and only differ in terms of surface friction and weight. In addition to the different materials, the wax beads and cotton balls have a tiny hole through them.

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

Figure 11.1: Products used for experiments.

For these products, image data using a miniature optical belt sorter was recorded. A detailed presentation of the system with the purpose of a simulation thereof is provided in [10]. The objects were fed into the system by a vibrating feeder, passing down a slide on to a conveyor belt running at 1.1 m/s. Frames were recorded at ∼192 Hz using a camera of the type *Bonito CL-400*. An example frame is provided in Figure 11.2.



(a) Wooden spheres

(b) Wooden hemispheres

Figure 11.2: Frames captured on the conveyor belt. The red, arrowed lines illustrate the resulting tracks in terms of associated measurements.

The conveyor belt has a total length of 60 cm. A crucial parameter for flow control is the length of the belt. Therefore, different lengths were imitated by mounting the camera at different positions along the belt at a fixed distance. More precisely, data was collected for 3 locations which are described in the following. The first section, hereafter referred to as *feeding*, is located right after objects enter the belt from the slide and covers the first ∼11 cm. Hence, this location simulates the shortest belt considered in this evaluation. The second section is located at the middle of the belt, covering the area reaching from ∼23 cm to ∼34 cm, and is referred to as *center* in the remainder. Lastly, the third section called *edge* covers the last ∼8 cm of the belt.

Each of the following processing steps were performed offline subsequent to image recording. First, basic image processing routines are required to extract the midpoints of potentially contained objects in each frame. For this purpose, the fact that a stable background as well as illumination exists in the scene is exploited. Utilizing a background subtraction approach, regions of the frame containing objects can be extracted and their midpoints calculated. This centroid's information is then fed into the multitarget tracking system, which outputs a list of tracks and the associated measurements for each data set. From this data, the feature vectors as described in the previous section are calculated.

Since manual feature selection was performed, Principal Component Analysis (PCA) is used to validate the selection. An example of the outcome is provided in Figure 11.3. As can be seen, visualising the first and second component shows that clusters form for all of the 4 classes.

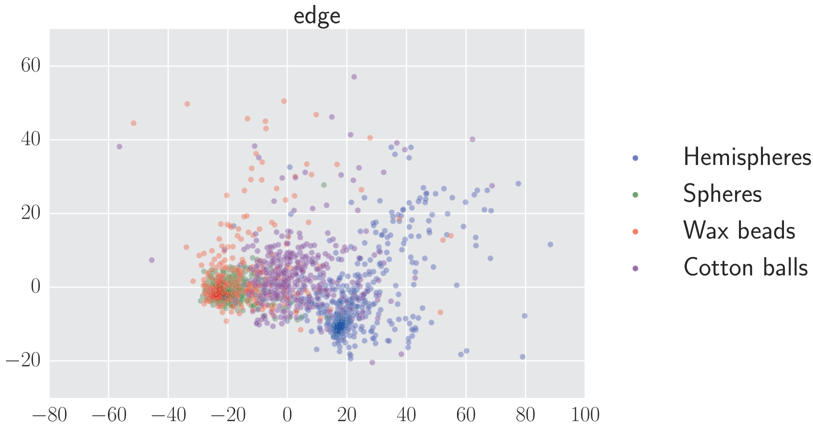


Figure 11.3: Visualisation of the feature space using the first and second component obtained via PCA for position *edge*.

4 Experimental results

In order to demonstrate the success of the method, a random forest classifier consisting of 10 estimators was trained on the data. As a measure of quality, Matthews correlation coefficient (MCC) [11] is used. Firstly, the entire data was used both for training and testing in order to estimate an upper bound of the performance. For all observation areas and classes, excellent values ranging between 0.98 and 1.0 were obtained. This clearly indicates that classes can be discriminated on basis of the data.

Secondly, training and testing via cross validation was performed. For this purpose, 60% of the data was used for training. Obtained results as shown in Figure 11.4 (b) allow for several conclusions. In general, wooden spheres and hemispheres can be detected the most accurately for all considered camera positions. It also becomes clear that classification performance increases with the length of the belt used for transportation. The latter is especially noteworthy since it leads to the conclusion that the differences in the adaption to belt velocity reveals properties which allow discrimination of the different products. A possible explanation, which is yet to be confirmed, is that at the beginning of the belt, the motion of objects is rather random due to the feeding process. In summary, results show that motion-based features are expressive key figures which can allow discrimination of products. Therefore, it is assumed that combining traditional features, such as color-based and geometric, with motion related ones results in a significant increase in classification performance and therefore minimization of the detection error in sensor-based sorting.

Furthermore, Figure 11.5 provides insights regarding the errors made during classification. For instance, from the confusion matrices, it can be seen that for the position *feeding* many wax beads are falsely classified as wooden hemispheres, while this error almost disappears for the position *edge*. However, the number of cotton balls mistakenly hold as wooden hemispheres can be observed to be almost equal for both positions.

5 Conclusion

In this paper, it was shown that motion-based features provide a powerful tool to discriminate certain products in sensor-based sorting. Therefore, the presented approach contributes towards minimizing the detection error. The approach was validated experimentally on the basis of real world data obtained using a miniature sorting system. Results indicate that the difference in adaption to the velocity of the conveyor belt reveals the most insightful properties that allow discrimination of the products.

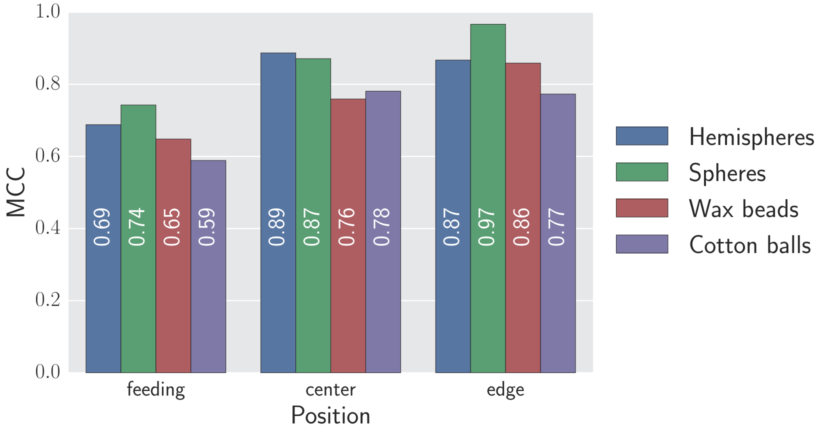


Figure 11.4: Classifier performance for cross validation (testing size 40%).

Due to the success of the method, it is intended to explore more complex motion-based features in the future. For instance, information regarding changes in direction and spin may lead to even better results. Also, for application in an industrial setting, further potential challenges, such as required computation time, need to be taken into consideration and addressed appropriately. Lastly, insights from this paper can be taken into account for system design. 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. This in turn requires precise predictions for physical separation. Hence, a potential conflict between quality of classification and separation exists.

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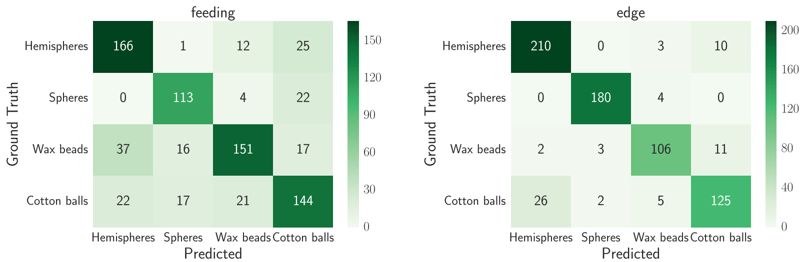

(a) Position *feeding*. (b) Position *edge*.

Figure 11.5: Confusion matrices for cross validation.

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