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

Improving Optical Sorting of Bulk Materials Using Sophisticated Motion Models

Verbesserung der optischen Schüttgutsortierung mittels verfeinerter Bewegungsmodelle

Abstract: Visual properties are powerful features to reliably classify bulk materials, thereby allowing to detect defect or low quality particles. Optical belt sorters are an established technology to sort based on these properties, but they suffer from delays between the simultaneous classification and localization step and the subsequent separation step. Therefore, accurate models to predict the particles' motions are a necessity to bridge this gap. In this paper, we explicate our concept to use sophisticated simulations to derive accurate models and optimize the flow of bulk solids via adjustments of the sorter design. This allows us to improve overall sorting accuracy and cost efficiency. Lastly, initial results are presented.

Keywords: Computational Fluid Dynamics, Discrete Element Method, Multi-Object Tracking, Optical Sorting

Zusammenfassung: Visuelle Eigenschaften sind mächtige Merkmale zur Klassifikation von Schüttgütern, auf Basis derer man defekte oder unbrauchbare Teilchen erkennen kann. Die Verwendung optischer Bandsortieranlagen ist eine etablierte Technik zur Sortierung basierend auf diesen Merkmalen. Derartige Sortierer leiden jedoch unter Verzögerungen zwischen der gleichzeitigen Klassifikation und Lokalisierung und der darauffolgenden Separation. Dadurch entsteht die Notwendigkeit für akkurate Modelle der Teilchenbewegung, mittels derer diese Lücke überbrückt werden kann. In dieser Veröffentlichung stellen wir unser Konzept vor, mittels hochentwickelter Simulationen genaue Modelle herzuleiten und den Teilchenstrom durch Optimierungen im Design des Sortierers zu verbessern. Dies ermöglicht die Verbesserung der Sortiergüte und Kosteneffizienz. Abschließend präsentieren wir erste Ergebnisse.

Schlagwörter: Diskrete Elemente Methode, Multi-Object Tracking, Numerische Strömungsmechanik, Optische Sortierung

***Corresponding Author: Florian Pfaff:** Intelligent Sensor-Actuator-Systems Laboratory, Karlsruhe Institute of Technology (KIT), Germany.
Benjamin Noack, Uwe D. Hanebeck: Intelligent Sensor-Actuator-Systems Laboratory, Karlsruhe Institute of Technology (KIT), Germany.
Christoph Pieper, Harald Kruggel-Emden, Siegmar Wirtz, Viktor Scherer: Department of Energy Plant Technology (LEAT), Ruhr-Universität Bochum (RUB), Germany.
Georg Maier, Robin Gruna, Thomas Längle, Jürgen Beyerer: Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (IOSB), Germany.

1 Introduction

Approximately 10% of all energy produced annually is spent on transport and handling of bulk material [1], making efficiency improvements highly valuable to the modern world. While some bulk materials can be sorted based on mechanical characteristics such as shape, size, and density, others can mainly be distinguished according to visual properties. An example for the latter are glass splinters, which are typically sorted based on their color. For these applications, sorting systems combining optical sensors with image processing technology and a subsequent separation step present a convenient solution. Optical sorting systems are often characterized by the applied transport system, with belt sorters and slide sorters being the most representative ones.

While non-optical sorters such as sieves and magnetic separators exploit differences in the physical characteristics of the bulk solids and combine classification and separation in one step, these tasks have to be regarded separately in optical sorters. This leads to the following key challenge. Due to delays emerging at various components of the system, a small, yet not negligible time gap (typically in the order of milliseconds) passes between classification and separation. The same applies to the localization, which is usually combined with the classification. Consequently, it is necessary to precisely predict when and where each particle arrives at the separation mechanism. This prediction necessitates models for the particles' motions. Until now, optical sorters have largely worked without explicitly modeling the particles' motion behavior. However, they have always implicitly relied on the very simple and often inaccurate assumption that all particles move at a predefined speed in the main transport direction.

In this paper, we present a novel interdisciplinary concept to tackle this deficiency. We illustrate concepts that allow us to make explicit use of sophisticated simulations and explicate a promising approach to achieve accurate motion models, which can be integrated into industrial optical sorters in the near future.

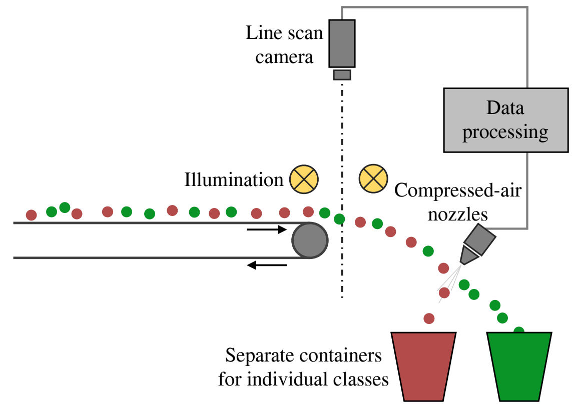


Fig. 1. Schematic view of an optical belt sorter.

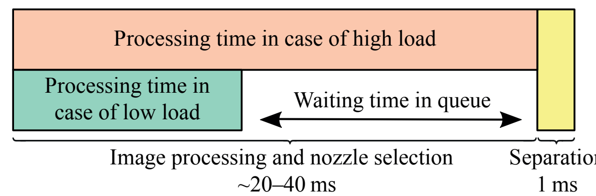


Fig. 2. Delays occurring between inspection and actual separation. For cases with even longer processing time, the system will not be in time to perform the separation.

2 State-of-the-art Optical Belt Sorters

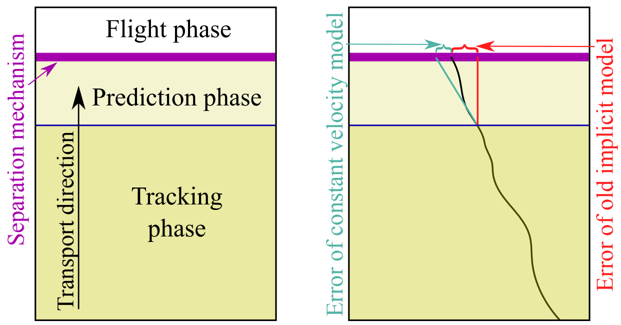
The basic components of a state-of-the-art optical belt sorter are illustrated in Fig. 1 and a detailed overview of the applied processing pipeline is provided in [2]. Particles of the bulk material are transported on a belt that serves the purpose of adapting the particles' velocities to its own speed and reducing movements perpendicular to the transport direction, which is crucial for current belt sorters. After leaving the belt, the particles fall off along a parabolic flight path. During their flight, they pass the so-called inspection line illuminated appropriately to the task at hand. At this point, particles are recorded with a line scan camera and the image data is processed with the goal of classifying and localizing each particle.

The classification result serves as the basis for the actual separation. Depending on the classification result, compressed air nozzles lined up in an array parallel to the inspection line are selectively activated to alter the flight path of certain particles. Due to differing amounts of particles and object properties, the time required for image processing varies as illustrated in Fig. 2. By activating the nozzles at a fixed delay after the particle passes the inspection line, current systems implicitly assume that all particles move at the same speed in the transport direction. The nozzle that is in line with the observed position is then selected for activation. Thus, it is assumed that the velocity component perpendicular to the transport direction is zero and that the velocity component in the transport direction is static and implicitly known.

Current optical belt sorters use imprecisely focused streams of air and activate the individual nozzles longer than necessary to account for the uncertainty in the particle's movement. Clearly, this comes at the cost of hitting additional particles located close to the intended particle, hence potentially producing high amounts of so-called *by-catch*, i.e., particles that are mistakenly blown out. To calculate precise control inputs for the separation mechanism, accurate models are needed as well as a better understanding of the particle–particle interaction, especially in cases of higher throughput of bulk solids.

3 Models

The easiest way to calculate the temporal and spatial offset from the time and place the particles are observed at is to assume that all particles have an identical and known motion pattern. This is done implicitly in current optical belt sorters explained in Sec. 2. However, this is clearly a rough approximation. Especially bulk materials that do not typically follow such a constant, linear motion violate this assumption to such an extent that sorting becomes infeasible using current optical belt sorters.



(a) Phases of the tracking.

(b) Error of the implicit model compared with the error of a constant velocity approach.

Fig. 3. Illustrations of the different phases of the tracking and of the occurring errors depending on the model used. For the old implicit model, we assume the inspection line to be at the blue line that separates the prediction and the tracking phase.

3.1 Predictive Tracking for Optical Belt Sorters

To alleviate this weakness, we have enhanced a prototype of an optical belt sorter by adding an area scan camera. We refer to this extension that allows us to make full use of the additional information obtained by the area scan camera as TrackSort [3, 4]. While the delays explained in Sec. 2 are not reduced by the use of an area scan camera, we gain a significant advantage by observing each particle at multiple time steps.

The tracking process to make use of the multiple observations can be divided into three phases that we can visualize on a top view as sketched in Fig. 3a. During the tracking phase, we expect to obtain measurements of all particles and can update our knowledge about each particle's position and velocity accordingly. The prediction phase is necessary due to the delays explained in Sec. 2. When a particle enters the prediction phase, the decision about whether to active the corresponding nozzle must have already been made. Therefore, we cannot rely on measurements during the prediction phase and have to use our acquired knowledge about the particle's motion to predict its movement. The multiple observations obtained during the tracking phase can not only help us make accurate predictions, but also facilitate improved classifiers.

In our current prototype, we solve the measurement-to-track association problem by maximizing the global association likelihood [5, Ch. 10.3] and use one Kalman filter per track with a constant velocity model to estimate each particle's position and velocity. The uncertainty of the system model was derived from empirical observations and the measurement uncertainty was obtained by analyzing the noise on recordings of static particles. Since visually matching particles from one time step to the next is computationally infeasible and often even theoretically impossible, we treat the measurements obtained by the area scan camera as unlabeled measurements. Problems of this kind are referred to as multitarget tracking problems [6, 5] without labels in literature. While multitarget tracking is challenging and still an active field of research, a constant velocity model that extrapolates the particle's position using the observed velocity (also including the velocity component perpendicular to the transport direction) suits the application well enough to allow us to use simple solutions. As sketched in Fig. 3b, the constant velocity model is an improvement compared with the old implicit model but still offers room for improvement.

3.2 Improving Models

Further optimization of the motion models used for the tracking is key to optimizing the system's performance. First, the prediction accuracy as the critical quality criterion strongly relies on an accurate model. Second, the measurement-to-track assignment of the multitarget tracking depends on the accuracy of the prediction of the particles' motions from one frame to the next.

For the latter, an accurate model can not only increase the probability of the assignment being correct, it also allows for significantly improving the run time performance of the system. The measurement-to-track assignment is computationally expensive and can even take up more CPU time than the image processing task if naïve algorithms are used. Using better models, we can refine a step called *gating* [7, Ch. 4] in which the problem is simplified and thus made faster to solve at the cost of a negligible risk of false assignments. Thus, even models that are computationally more costly can have a net benefit on the run time performance of the system, allowing us to track more particles concurrently and facilitate the use of cameras with higher frame rates.

To derive improved models for the tracking, our first aim is to model the entire system as accurately as possible using realistic, three-dimensional physical models considering particle–particle as well as particle–wall interactions. Such simulation approaches could be the Discrete Element Method (DEM) coupled with Computational Fluid Dynamics (CFD) as introduced in the next section. By having an accurate simulation at our disposal, we can first improve our constant velocity model. For example, using a simulation with a high resolution that respects all dimensions, we can accurately derive the system uncertainty without the need for extensive experiments. In the second step, we aim to derive new simplified models. These models may vary for different bulk materials. We can safely rely on the classification decision because if the classification is incorrect, using an incorrect prediction model will be unlikely to do any harm. If an incorrect classification results in targeting one particle using the nozzles although the correct decision is to not alter its flight path, then an incorrect prediction will even give it a slightly better chance to escape the attempted separation. If the decision not to target the particle with the separation mechanism is made, then the predicted position will be discarded and thus will not induce any effect on the sorting performance.

3.3 Simulation With a Coupled DEM–CFD Approach

In order to improve the motion models for the tracking and to get a more detailed understanding of the bulk solid's behavior in optical sorters as well as to potentially improve the design of optical sorters, particle-based simulation approaches like the Discrete Element Method (DEM) are applicable. The DEM was first introduced by Cundall and Strack in 1979 [8]. It allows the detailed analysis of particle–particle and particle–wall interactions. The translational and rotational motion of each particle, also allowing non-spherical shapes, is calculated using Newton's and Euler's equations of motion and can be written as

$$m_i \frac{d^2\vec{x}_i}{dt^2} = \vec{F}_i^c + \vec{F}_i^{pf} + \vec{F}_i^g \ , \tag{1}$$

$$\hat{I}_i \frac{d\vec{W}_i}{dt} + \vec{W}_i \times (\hat{I}_i \vec{W}_i) = \Lambda_i^{-1} \vec{M}_i \ , \tag{2}$$

where m_i is the particle mass, $d^2\vec{x}_i/dt^2$ the particle acceleration, $\vec{F}_i^c$ the contact force, $\vec{F}_i^g$ the gravitational force, and $\vec{F}_i^{pf}$ the particle–fluid force, which is required to model the particle–fluid interaction at the particle ejection stage of the sorter. The second equation gives the angular acceleration $d\vec{W}_i/dt$ as a function of the angular velocity $\vec{W}_i$, the external moment resulting out of contact of particle/fluid forces $\vec{M}_i$, the inertia tensor along the principal axis $\hat{I}_i$, and the rotation matrix converting a vector from the inertial to the body fixed frame Λ_i^{-1}. Information regarding the time-resolved position, velocity, and orientation of every particle enables the investigation of attainable selectivity and throughput of the optical sorter. The data can further be used to optimize the employed particle tracking by deriving improved motion models.

To model the particle ejection by bursts of compressed air, the DEM is coupled with Computational Fluid Dynamics (CFD). The fluid phase is described by solving the volume averaged Navier–Stokes equations

$$\frac{\partial(\epsilon_f \rho_f)}{\partial t} + \bigtriangledown(\epsilon_f \rho_f \vec{u}_f) = 0 \ , \tag{3}$$

$$\frac{\partial(\epsilon_f \rho_f \vec{u}_f)}{\partial t} + \bigtriangledown(\epsilon_f \rho_f \vec{u}_f \vec{u}_f) = -\,\epsilon_f \bigtriangledown p + \bigtriangledown(\epsilon_f \tau) + \epsilon_f \rho_f \vec{g} + \vec{f}_{int} \tag{4}$$

and thus, we do not resolve the flow around individual particles. Here, $\vec{u}_f$ is the physical fluid velocity, ρ_f is the density, p is the pressure, $\vec{f}_{int}$ is the volumetric particle/fluid interaction momentum source employed in each CFD cell, ϵ_f is the local fluid porosity, and τ is the fluid viscous stress tensor. Previous studies, like one recently conducted by Fitzpatrick et al. [9], show that this approach can correctly describe the complex particle–fluid interaction.

The optical belt sorter used for experimental investigations modeled within the DEM framework is shown in Fig. 4a. For initial experiments and validation purposes, the system is first run in batch operation and without particle ejection and consequently sorting. During first investigations, a base case is defined and different operating parameters such as particle throughput and shape, belt velocity and length as well as the amplitude of the vibrating feeder are altered in both experiments and simulations. Analysis and comparison of particle velocities, orientations, and trajectories validate the simulation and provide first insights into the general system behavior. Initially, different model shapes and their corresponding behaviors are examined (Fig. 4b-d) and it is planned to numerically model and investigate real bulk solids such as coffee beans, rice, and glass shards in the near future.

Based on the obtained information regarding the particle behavior, the improved particle tracking, and the insights into the particle ejection process, we aim to develop a numerical model of the entire new optical sorter that includes the sorting decisions and sorting process. This model will allow the detailed analysis of every stage of the sorting process and will help to gain insights which would be difficult or expensive to obtain experimentally. In short, the model can be used as a versatile design tool and for further process optimization.

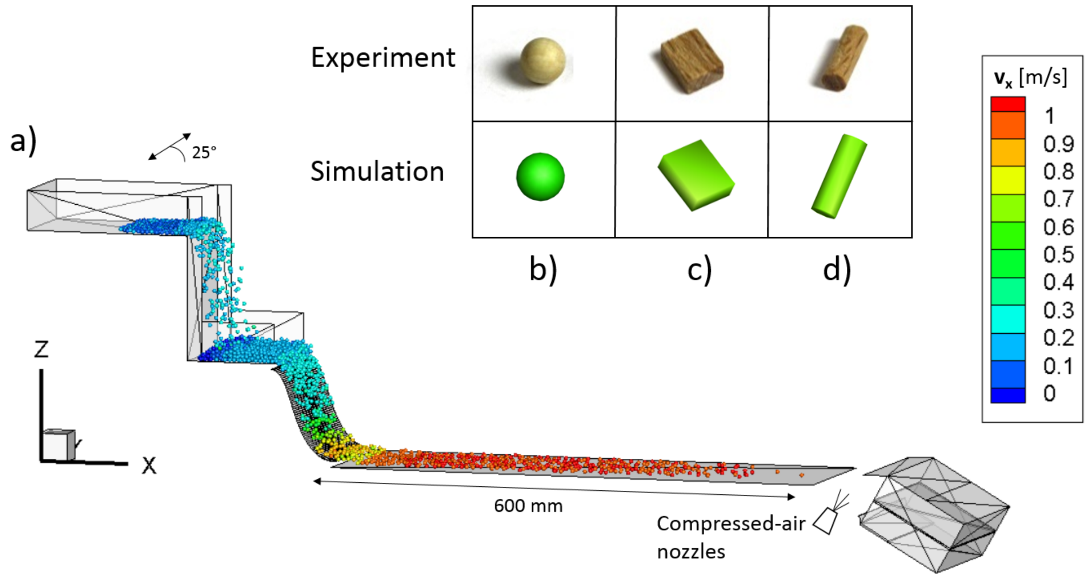


Fig. 4. DEM simulation of the optical belt sorter (a) and different particle shapes (b-d) employed in experiments and simulations. The colors of particles on the belt indicate their velocities in the transport direction.

4 Initial Results

While we are still at an early phase of the project, we have laid the basic building blocks and already attained two objectives that we explain in more detail in this section. One objective was to build a tool to test the tracking approach using a simple model on recorded image data. The other task was to develop a first DEM model for initial simulations to confirm the suitability of this approach.

4.1 Tracking Using a Constant Velocity Model

For our first experiments, a simple tracking algorithm was implemented in rapid prototyping programming languages. Using common image processing techniques such as connected component analysis, we separate the particles of the bulk material from the background. Following that, we calculate certain geometric features, for instance their approximate centroids, which are passed on to the multitarget tracking. In each data set, only particles of a single bulk material were used and our goal was merely to test the feasibility of the tracking and measure first improvements by the constant velocity model.

As shown in Fig. 5, our assignments are highly accurate, implying that we are able to predict the next measurement with high precision. This suggests that the utilized multitarget tracking algorithm is well suited to the problem at hand. Nonetheless, we are planing on evaluating other multitarget tracking algorithms such as the JPDAF [10] by using very fast approximations [11, 12] and investigating more expensive algorithms [13, 14] for low numbers of particles. A more in-depth analysis of our results using the constant velocity model is given in [3].

4.2 DEM Simulations

Initial simulations with the DEM model described in Sec. 3.3 offer first insights into particle and system behavior. At first, only the vibrating feeder, slide, and conveyor belt are considered. The obtained information also allows a detailed comparison with corresponding experiments. As the simulations are initially conducted in batch operation, knowledge of the particle mass flow within the sorter is of great importance. Fig. 6 shows the particle mass flow in the simulation measured at the beginning of the conveyor belt. The simulation is performed with 50 g of 5 mm wood spheres (Fig. 4b) while the vibrating feeder is set to an amplitude of 0.5 mm at 50 Hz and the conveyor belt moves at a velocity of 1.5 m/s. The graph in Fig. 6 shows that the particle mass flow between the 5 and 9 second mark is nearly constant at a value around 0.008 kg/s. Hence, the mass flow in this time frame can be regarded as stationary, which enables a system analysis neglecting time dependencies.

A screenshot of the conveyor belt, taken from the simulation, can be seen in Fig. 7. The vectors attached to the particles show the velocity and the direction of the

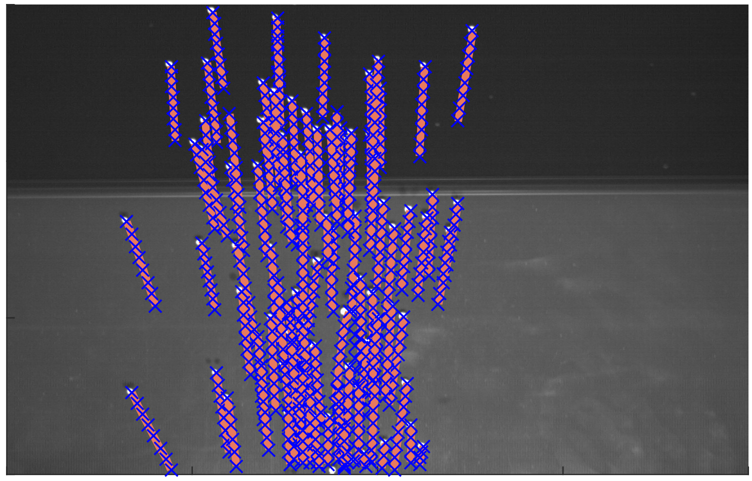


Fig. 5. The result of our prototypical tracking algorithm is visualized on an actual frame of a recorded dataset. The motion of each particle is visualized as the path (red) of the eight most recent position estimates (blue). That all motion paths are plausible implies that the measurement-to-track assignments are correct in this example.

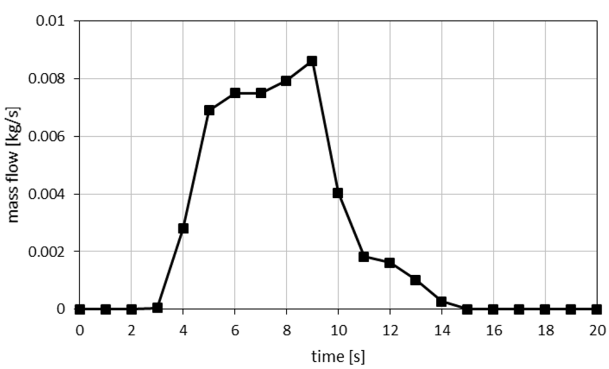


Fig. 6. Particle mass flow within the optical sorter obtained at the beginning of the conveyor belt.

movement while the particles' colors indicate their angular velocities. The figure shows that most of the spheres move parallel to the belt without any cross movements. Some exceptions are highlighted in the box on the right. These particles also have high angular velocities, originating from particle–particle and particle–wall interactions. Cross movements and particle interactions are expected to drastically increase when applying higher mass flows and when sorting bulk solids with higher tendencies to move perpendicular to the transport direction. The analysis of these and other system parameters form the basis of further investigations and tracking model improvements.

5 Conclusions

Using an area scan camera to observe each particle at multiple time steps has great potential for improving the separation using improved predictions of the particles' positions. To make optimal use of the additional data obtained and optimize run time efficiency, accurate models are essential.

Not only will the DEM–CFD approach help us derive accurate models, it will also allow us to optimize every single step of the sorting process. By being able to simulate the whole process accurately, we can not only derive models, but also ensure that mechanical and structural parts are built in a way that ensures that the particles' motions adhere to the derived models.

One goal of our research is to improve the probability of hitting targeted particles, reducing by-catch, and saving energy in the separation process by reducing the amount of compressed air used. The other objective is to optimize the optical belt sorter regarding throughput, necessary space, and cost while maintaining a sorting quality that suits the needs of the users of optical belt sorters.

Acknowledgment: The IGF project 18798 N of the research association Forschungs-Gesellschaft Verfahrens-Technik e.V. (GVT) was supported via the AiF in a program to promote the Industrial Community Research and Development (IGF) by the Federal Ministry for Economic Affairs and Energy on the basis of a resolution of the German Bundestag.

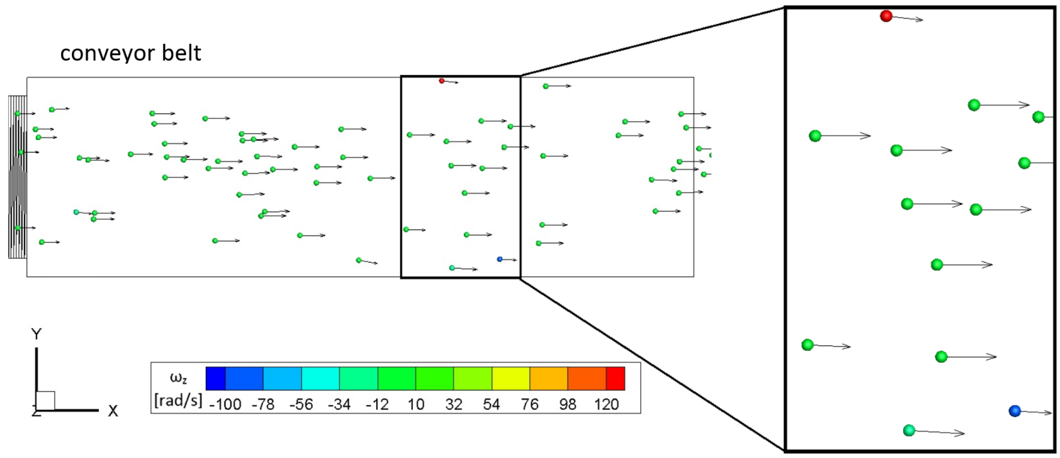


Fig. 7. DEM simulation with 5 mm wood spheres showing the top view of the conveyor belt. The vectors indicate the direction of the movement and the particles' colors describe their angular velocities.

Danksagung: Das IGF-Vorhaben 18798 N der Forschungsvereinigung Forschungs-Gesellschaft Verfahrens-Technik e.V. – GVT, Theodor-Heuss-Allee 25, 60486 Frankfurt am Main wurde über die AiF im Rahmen des Programms zur Förderung der Industriellen Gemeinschaftsforschung (IGF) vom Bundesministerium für Wirtschaft und Energie aufgrund eines Beschlusses des Deutschen Bundestages gefördert.

References

[1] Jacques Duran. *Sands, Powders, and Grains: An Introduction to the Physics of Granular Materials*. Springer, New York, 2000.

[2] Matthias Richter, Thomas Längle, and Jürgen Beyerer. An approach to color-based sorting of bulk materials with automated estimation of system parameters. *tm -Technisches Messen*, 82(3):135–144, 2015.

[3] Florian Pfaff, Marcus Baum, Benjamin Noack, Uwe D. Hanebeck, Robin Gruna, Thomas Längle, and Jürgen Beyerer. TrackSort: Predictive Tracking for Sorting Uncooperative Bulk Materials. In *Proceedings of the 2015 IEEE International Conference on Multisensor Fusion and Information Integration (MFI 2015)*, San Diego, California, USA, September 2015.

[4] Robin Gruna, Kai-Uwe Vieth, Henning Schulte, Thomas Längle, Uwe D. Hanebeck, Marcus Baum, and Benjamin Noack. Fördersystem, Anlage zur Schüttgutsortierung mit einem solchen Fördersystem und Transportverfahren, September 3 2015. WO Patent App. PCT/EP2015/052,587.

[5] Ronald PS Mahler. *Statistical Multisource-Multitarget Information Fusion*. Artech House, Inc., 2007.

[6] Samuel Blackman and Robert Popoli. *Design and Analysis of Modern Tracking Systems*. 1999.

[7] Martin Liggins II, David Hall, and James Llinas. *Handbook of Multisensor Data Fusion: Theory and Practice*. CRC press, 2 edition, 2009.

[8] Peter A. Cundall and Otto D. L. Strack. A Discrete Numerical Model for Granular Assemblies. *Géotechnique*, 29(1):47–65, 1979.

[9] Robert S. Fitzpatrick, Hylke J. Glass, and Richard D. Pascoe. CFD–DEM modelling of particle ejection by a sensor-based automated sorter. *Minerals Engineering*, 79:176–184, 2015.

[10] Yaakov Bar-Shalom, Fred Daum, and Jim Huang. The Probabilistic Data Association Filter. *IEEE Control Systems*, 29(6):82–100, December 2009.

[11] Marcus Baum. Linear-time JPDAF based on many-2-many approximation of marginal association probabilities. *Electronics Letters*, 51(19):1526–1528, 2015.

[12] Kevin Romeo, David F. Crouse, Yaakov Bar-Shalom, and Peter Willett. The JPDAF in Practical Systems: Approximations. In *SPIE Defense, Security, and Sensing*, pages 76981I–76981I. International Society for Optics and Photonics, 2010.

[13] Marcus Baum and Uwe D. Hanebeck. The Kernel-SME Filter for Multiple Target Tracking. In *Proceedings of the 16th International Conference on Information Fusion (Fusion 2013)*, Istanbul, Turkey, July 2013.

[14] Gerhard Kurz, Marcus Baum, and Uwe D. Hanebeck. Real-time Kernel-based Multiple Target Tracking for Robotic Beating Heart Surgery. In *Proceedings of the Eighth IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM 2014)*, A Coruña, Spain, June 2014.