ParticleTracking: A GUI and library for particle tracking on stereo camera images

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Summary

The ParticleTracking software is intended to facilitate semi-automatic detection, 3D position and orientation reconstruction and tracking of arbitrarily shaped particles from 2-view stereo camera footage. The software consists of two packages, RodTracker and ParticleDetection. The ParticleDetection package provides functionality for training and application of neural networks (e.g. Mask R-CNN) for particle detection in camera images, as well as automatic 3D matching and multi-object tracking of these particles. The RodTracker package is a graphical user interface (GUI) for the particle tracking task, encapsulating the functionality of ParticleDetection and providing means to manually correct the automatically generated particle coordinates and tracking data.

The main features of this software are given below with a more extensive feature description available in the documentation under https://particletracking.readthedocs.io/en/latest/:

- training and application of (Detectron2) Mask R-CNN models for detecting particles on images
- automated particle endpoint localization from segmentation masks
- automated assignment of particle correspondences (3D matching) between two camera views
- reconstruction of 3D coordinates and orientations of particles identified on camera images
- automated tracking of particles over multiple stereo camera frames, i.e. the course of an experiment
- providing a GUI for applying manual corrections to the automatically generated data with a typical workflow shown in Figure 1

The main focus of this software is currently on elongated (rod-shaped) particles, but it is extensible with new particle geometries. The software can also be modified for inclusion of additional camera views for more accurate 3D tracking, or for 1-view 2D particle tracking. The RodTracker software is currently employed for data extraction in the German Aerospace Center (DLR) projects EVA II (50WK2348), VICKI (50WM2252), and CORDYGA (50WM2242). Recently, it was used in research article on cooling of granular gas mixture in microgravity (Puzyrev et al., 2024). Other publications that use this library for data extraction are currently in preparation. The prototype software for particle detection and tracking was described in (Puzyrev et al., 2020).

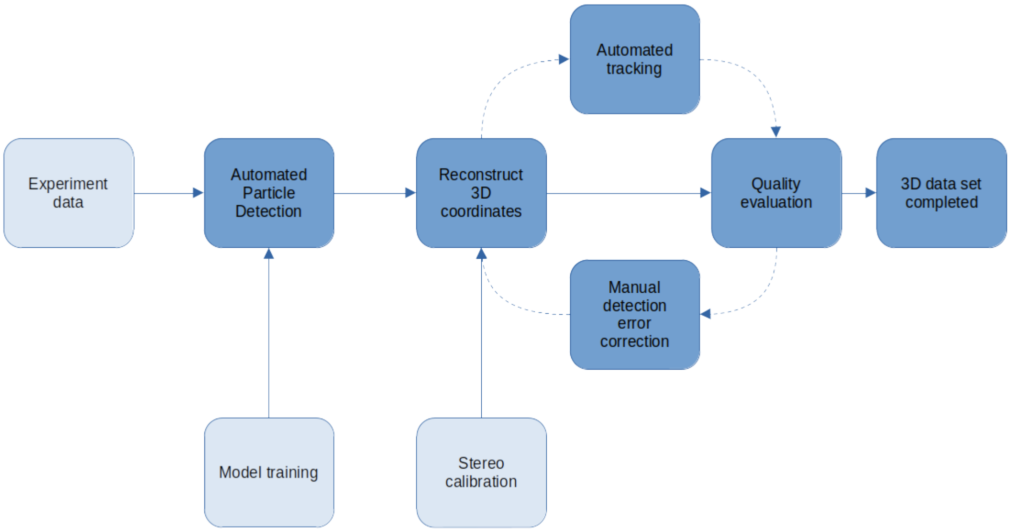

Figure 1: Typical workflow with the `RodTracker` for data extraction.

Statement of need

Many natural and industrial processes deal with granular gases, i.e. dilute ensembles of macroscopic particles floating and colliding in space. One of the defining features of such systems is inelasticity of the collision, i.e. dissipation of particle kinetic energy. This leads to fascinating phenomena such as spontaneous clustering, absence of energy equipartition and non-Gaussian velocity distributions. While most of 2D experiments can be performed in normal gravity, 3D experiments with granular gases require microgravity conditions. Starting from the pioneering results on cluster formation (É. Falcon et al., 1999), 3D experiments have been reported for spherical grains (E. Falcon et al., 2006; Yu et al., 2020), ellipsoids (Pitikaris et al., 2022) and rods (K. Harth et al., 2013; Kirsten Harth et al., 2018).

In typical microgravity experiments, ensembles of particles are placed in the container, excited mechanically or magnetically and observed with a stereo-camera setup. Many experiments were performed in the VIP-Gran instrument by the Space Grains ESA Topical team (spacegrains.org) during parabolic flight campaigns. In the majority of VIP-Gran experiments, particle density does not allow for tracking individual grains.

Another possibility is to perform the experiment with dilute ensembles, where most particles can be directly observed on video footage (Kirsten Harth et al., 2018; Puzyrev et al., 2020). In this case, the focus has been on experiments with elongated particles, due to the fact that collision rates for such particles are much higher than for spheres for the same packing fraction. Thus, even if particles overlap on the camera views, usually their endpoints still can be observed and their 3D positions and orientations can be reconstructed. In addition, study of elongated particles allows to observe the evolution of their orientations and to find the kinetic energy associated with the rotational degrees of freedom. Experiments with more complex particle types, such as spatial crosses (hexapods) were recently performed as well.

For the study of such systems, it is beneficial to know the 3D positions and orientations over time for as many particles as possible. To achieve statistically meaningful results, the tracking of many tens to hundreds of particles is usually required. With that information, a reliable statistical analysis of the ensemble properties and their evolution over time can be achieved. Due to the large number of simultaneously tracked objects and their relatively high velocity, accurate experimental data analysis requires high frame rates. In one drop tower experimental run, around 9 seconds of 100 to 240 fps video footage must be analyzed. This makes manual data analysis exceptionally time-consuming.

An overview of challenges and methods of visual analysis of 3D granular systems is provided in (Schroeter et al., 2022). In case of relatively simple particles shapes, for automatic 2D detection and tracking tasks the common image processing tools can be used, including Fiji (Schindelin et al., 2012) with TrackMate plugin (Ershov et al., 2022) or ilastik (Berg et al., 2019).

In case of more complex particle shapes, i.e. rod-like particles, more elaborate custom workflows are employed. Due to the large number of overlapping particles, conventional particle detection methods based on color separation, morphological operations, and Hough transform have proven to be unstable.

For this reason, an AI-assisted approach based on Matterport Mask R-CNN implementation (Abdulla, 2017; He et al., 2017) has been suggested (Puzyrev et al., 2020) for extraction and processing of data from the raw stereo camera images. This approach still suffered from long manual data processing times, due to the necessity to correct remaining errors after automatic particle detection, matching and tracking, as well as a suboptimal user interface to perform the correction tasks.

The `ParticleTracking` software is an evolution of the AI-assisted framework for the analysis of dilute granular ensembles, improved by the transition to the Detectron2 platform, inclusion of the `RodTracker` GUI, and a documented and extensible codebase. Our aim is to provide a solution which allows to perform several interconnected analysis steps, namely 2D particle detection, data labeling/correction, and 3D reconstruction/tracking in one software interface.

As an alternative, individual data analysis steps can be performed with the other methods and integrated into `ParticleTracking` workflow, either with data import/export or source code modification. For example, experimentation with intelligent segmentation and tracking solutions such as SAM 2/ SAMURAI (Ravi et al., 2024; Yang et al., 2024) might provide useful results. Data correction and labeling can be performed in various image annotation tools, see, for example, the list here: https://github.com/HumanSignal/awesome-data-labeling. Note that for further processing in `RodTracker`, one should account for the necessity of labeling both endpoints in case of elongated particles and export the data in correct format as explained in `ParticleTracking` documentation. The 3D tracking task can be performed by implementing custom user scripts using MATLAB (one can start with (Himpel et al., 2011) and following articles) or OpenCV functions (as in `ParticleDetection` package).

Dependencies

Among others, the software depends on the following open source libraries: For 2D particle detection the Detectron2 (Wu et al., 2019) framework is used. For tracking the software relies heavily on functions provided by numpy (Harris et al., 2020), scipy (Virtanen et al., 2020) and PuLP (Roy et al., 2024). The GUI was constructed with PyQt5 and is using pandas (The pandas development team, 2022) for its data management.

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