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Segmenteverygrain: A Python module for segmentation of grains in images

Zoltán Sylvester [1,2¶], **Daniel F. Stockli** [2], **Nick Howes**[3], **Kalinda Roberts**[4], **Matthew A. Malkowski** [2], **Zsófia Poros**[5], **Rowan C. Martindale** [2], and **Wilson Bai**[2]

1 Bureau of Economic Geology, Jackson School of Geosciences, The University of Texas at Austin, Austin, TX, USA **2** Department of Earth and Planetary Sciences, Jackson School of Geosciences, The University of Texas at Austin, Austin, TX, USA **3** The Water Institute, New Orleans, LA, USA **4** BSC Group, Boston, MA, USA **5** ConocoPhillips, Houston, TX, USA ¶ Corresponding author

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Software

- Review
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Reviewers:

- @pr4deepr
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Summary

`Segmenteverygrain` is a Python module that addresses the need for quantifying grain size in granular materials. It combines the `Segment Anything Model` (SAM) with a U-Net-style convolutional neural network to detect and measure grains or clasts in diverse image types, ranging from photomicrographs of sand, mineral grains, and thin sections to photographic images of gravel and boulder fields. `Segmenteverygrain` supports segmentation of large images, georeferencing, and interactive editing of the results.

Statement of need

Grain size and shape are key parameters that influence the physical and chemical properties of granular materials. Quantitative estimates of these parameters are important in a number of fields, including:

- geomorphology, sedimentology, stratigraphy, paleontology;
- subsurface reservoir quality;
- structural geology, petrology and geochemistry;
- civil engineering;
- environmental science;
- materials science.

In recent years, numerous studies have illustrated the promise of automated image analysis and/or machine learning (ML) approaches (Azzam et al., 2024; Buscombe, 2020; Chen et al., 2023; Mair et al., 2022, 2024; Prieur et al., 2023; Tang et al., 2020). While these studies clearly show that ML techniques are superior to both manual data collection and conventional image processing techniques (e.g., Purinton & Bookhagen, 2021), they focus on a narrow range of image types, e.g., gravel on fluvial bars (Mair et al., 2022, 2024), boulder fields on planetary surfaces (Prieur et al., 2023; Robin et al., 2024), or petrographic images (Azzam et al., 2024; Tang et al., 2020).

With the emergence of large image segmentation models trained on millions of images (e.g., Kirillov et al., 2023; Ravi et al., 2024), the opportunity arises to use these models to detect a variety of grains in a broad range of image types. `Segmenteverygrain` is a Python module that takes advantage of the Segment Anything Model (SAM) (Kirillov et al., 2023) and uses a U-Net-style convolutional neural network to create prompts for SAM. It ensures that the resulting masks contain no duplicates and do not overlap. In general, SAM masks are more robust and accurate than the U-Net output (Figure 1). The U-Net model uses patches as input and output; to reduce edge effects, Hann-window-based weighting is used on overlapping patches (Pielawski & Wählby, 2020). The U-Net model was trained on 66 images of a variety of grains, split into 44,533 patches of 256x256 pixels. When compared to other approaches to grain size data collection, one of the advantages of `Segmenteverygrain` is that it is relatively easy to generate new training data and fine tune the U-Net model to improve the SAM output.

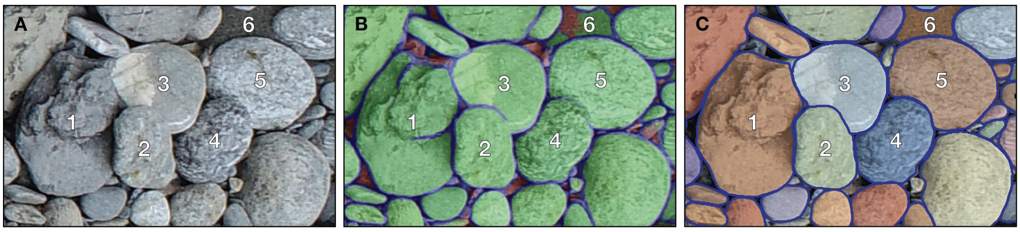

Figure 1: Photo of fluvial gravel (A), output of the U-Net segmentation (B), and the result of the SAM segmentation (C). The SAM segmentation correctly identifies grain 1 as a single object, separates grain 2 from grain 3 and grain 4 from grain 5, and incorrectly identifies a patch of the background as a grain (6). Image from Mair et al. (2022).

`Segmenteverygrain` has been successfully used on:

- images of boulder fields on asteroids (Robin et al., 2024);
- photographs of gravel and cobbles on beaches (Roberts, 2024) and fluvial bars (Figure 2);
- photomicrographs of sandstone (Figure 3) and oolitic limestone thin sections;
- photomicrographs of sand and detrital zircon grains.

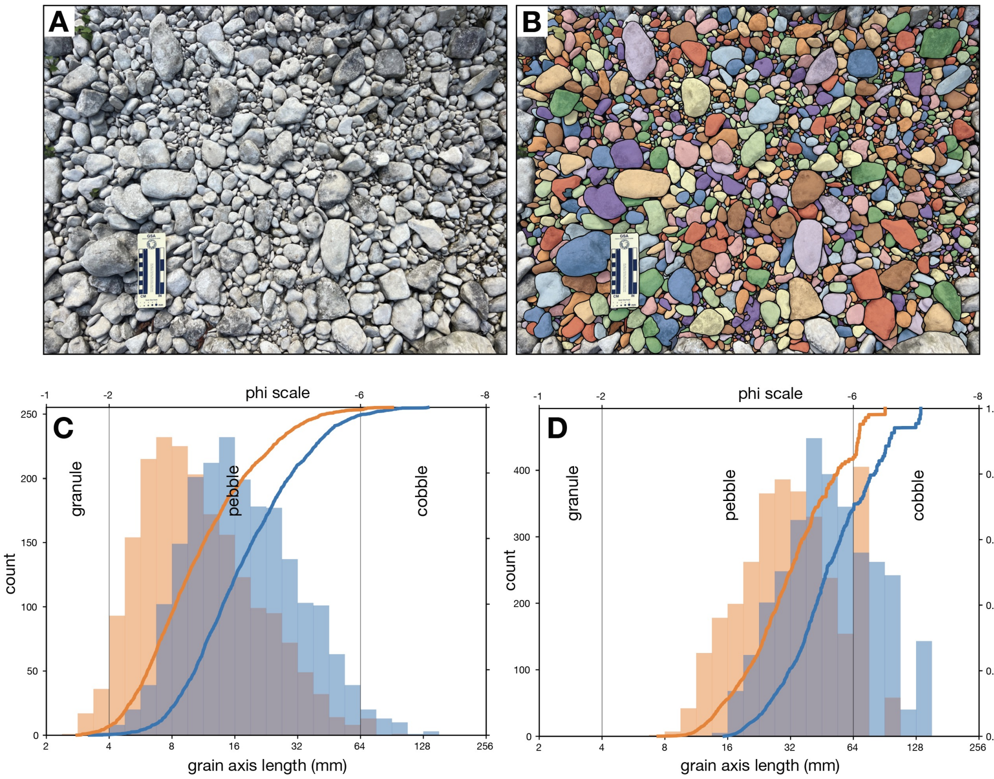

Figure 2: Photo of fluvial gravel (A), output of the segmentation (B), size distributions of the major and minor grain axes (C), and the area-weighted size distributions (D). Major grain axis lengths are shown in blue, minor grain axis lengths in orange. Photo taken by first author at Barton Creek, Texas.

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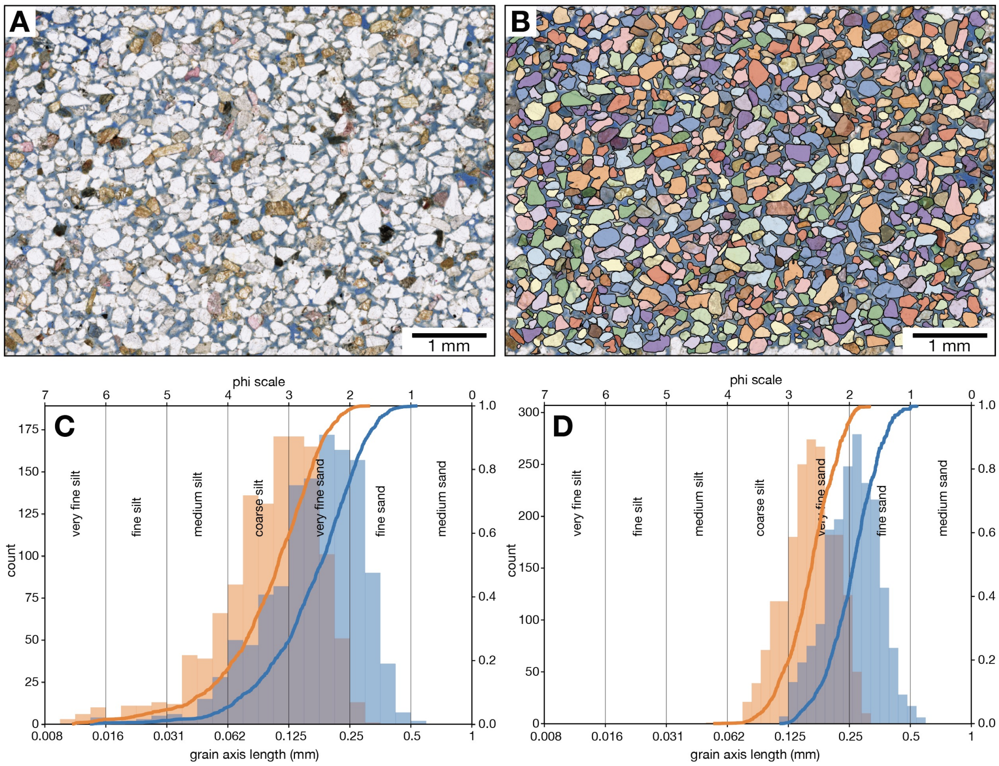

Figure 3: Photomicrograph of a sandstone in thin section (A), output of the 'Segmenteverygrain' segmentation (B), size distributions of the major and minor grain axes (C), and the area-weighted size distributions (D). Photomicrograph from Prodanovic et al. (2019).

Key functionality

The U-Net model in the `Segmenteverygrain` repository works relatively well on a variety of image types. However, it is recommended to first test it on a small image. If additional fine tuning is necessary, `Segmenteverygrain` has tools for interactively deleting, merging, and adding grains to generate training data.

The `predict_large_image` function can be used to run the segmentation of larger images that contain thousands of grains. This is done by running the U-Net + SAM predictions on smaller tiles of the input image, and collecting the grains into a list without duplicates.

Grain area, major and minor axis lengths, and a number of other grain features are stored in a dataframe. The distributions of major- and minor grain axis lengths are plotted; they can be weighted by grain areas, so that they are more consistent with grain size distributions that come from sieving, point counting, or Wolman counts (Taylor et al., 2022).

The `Segment_every_grain_w_georeferencing.ipynb` notebook demonstrates how to run `Segmenteverygrain` on a georeferenced image and save the results as a shapefile. This enables geospatial analyses of the coarse material, capturing variations in grain size across surfaces (Figure 4).

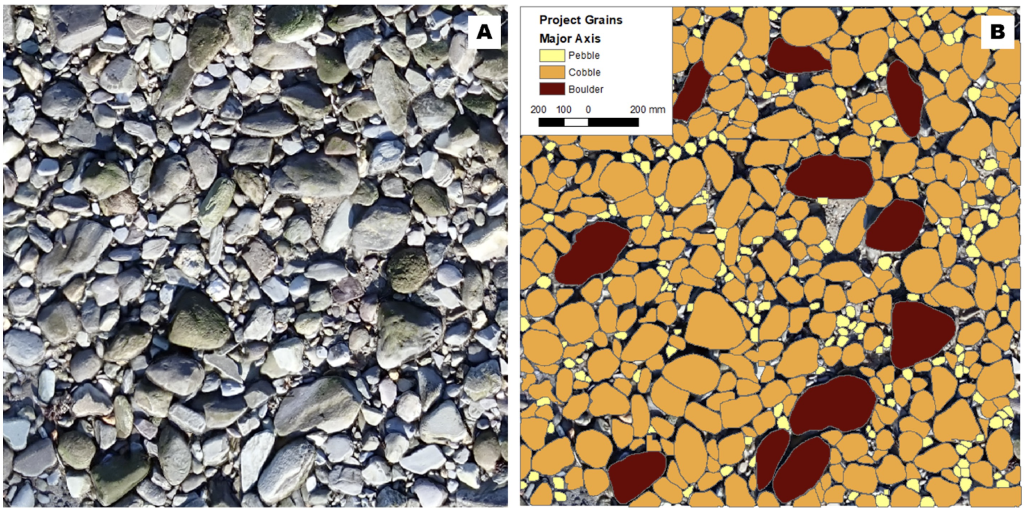

Figure 4: (A) Orthoimagery from ground-based structure-from motion survey of mixed sand and gravel beach. (B) Orthoimagery overlain with segmented grains colored by Wentworth size classes. Data from Roberts (2024).

Dependencies and availability

The `Segmenteverygrain` package is available from PyPI at https://pypi.org/project/segmenteverygrain/. The dependencies include image processing and shape manipulation tools, such as `Pillow` (Clark, 2015), `scikit-image` (Van Der Walt et al., 2014), `rasterio` (Gillies & others, 2013--), and `shapely` (Gillies et al., 2025). To identify and manipulate overlapping polygons, we rely on the `networkx` package (Hagberg et al., 2008). The U-Net model is built using `tensorflow` (Abadi et al., 2015) and `keras` (Chollet & others, 2015); parts of the ML workflow rely on the `scikit-learn` library (Pedregosa et al., 2011).

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