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Background and Motivation

The size and shape of sediment grains is critical for understanding the interactions between hydraulics and sediment transport. However, data on grain size is laborious to obtain. Therefore, "Photosieving" was developed, but still shortcomings persist.



Data on grain size is laborious to obtain, e.g., by manual counting in the field. (Bunte & Abt, 2001)



Method, Workflow and Data

Idea: Improve segmentation performance through transfer learning and train case-specific models instead of one large model.







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> State-of-the-art segmentation model > Trained on hundreds of biomedical images > Fast & flexible, open-source

Segmentation Performance



Evaluating average precision (AP) at intersection-over-union (IoU) thresholds of model predictions vs. labels.

Automated and flexible measuring of grain size and shape in images of sediment with deep learning David Mair¹, Ariel Henrique Do Prado¹, Philippos Garefalakis^{1,} Guillaume Witz^{2,} Fritz Schlunegger¹

- Often 'black box' approach when texture-based - Under-/over-segmentation when segmentation-based - Variability in images limits generalization ability - Large amounts of data needed (for machine learning)

Visual complexity in images of fluvial channel sediments alone. Images from Chen et al. (2022) and Mair et al. (2022).



 D_{50} b-axis (mm)

< 15

>15 - 20

> Transfer learning: Re-trained with images of fluvial pebbles, outcrops, periglacial sediments, and images from a gravel pit.





AP: 0.36



GrainID



AP: 0.18



PC_{auto}

- > Our segmentation models outperform benchmark methods in the test data.
- > The segmentation performance is controlled by dataset composition & training strategy.



> Over 268'000 individual grains measured.

> Less than 2h for fully automated analysis.

> Full grain size distribution for each tile.

Grain Size Results

Automated size mapping



Published in Dec. 2023 in arth Surface Processes and Landforms (ESPL)



A major update is in development, which will allow for more flexible custom model training and will include more specialist models for a wider range of settings.







References

Precentile D50 map for a gravel bar in the Swiss Kander River.



Outlook

Segmentation results for a range of settings and image types.

Bunte, K. and Abt, S. R. - https://doi.org/10.2737/RMRS-GTR-74, 2001

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