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Generating a pixel-wise annotated training dataset to train ML algorithms for mineral identification in rock thin sections

Jiaxin Yu[1*], Joyce Schmatz[2], Marven von Domarus[3], Mingze Jiang[1,4], Simon Virgo[1], Bastian Leibe[3], Florian Wellmann[1]

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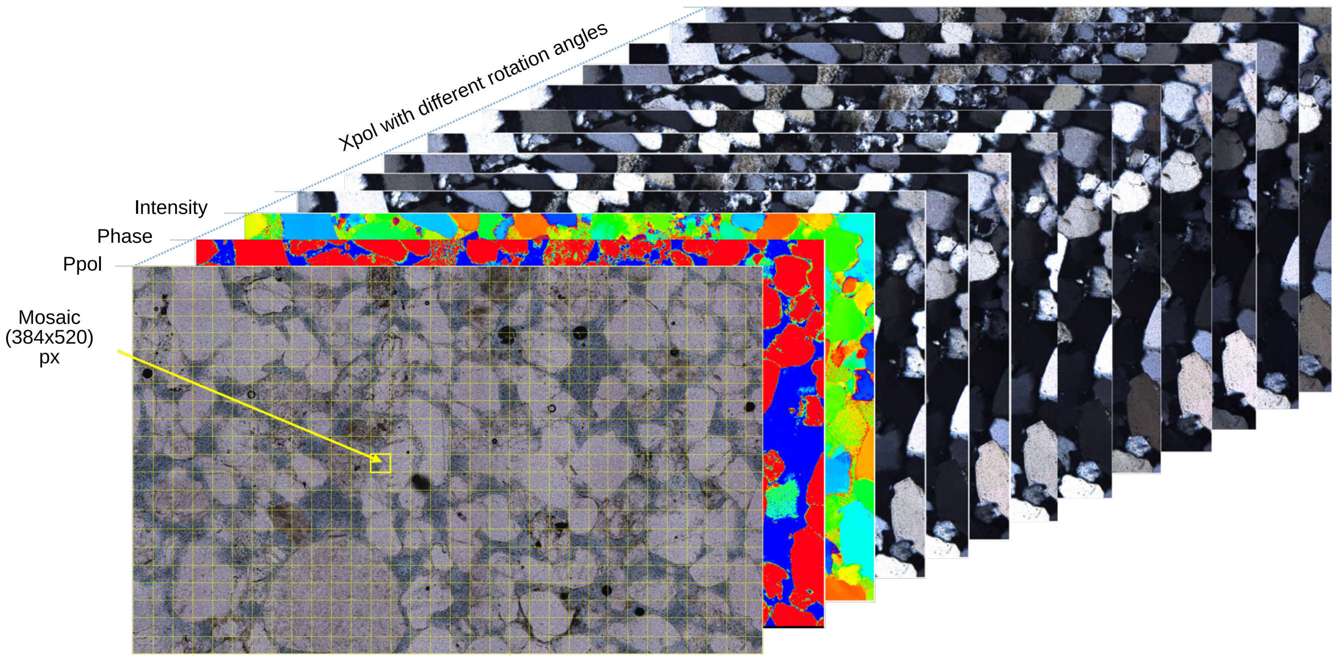
Motivation

Mineral thin sections contain a treasure of information. It is anticipated that thin section samples can be systematically and quantitatively analyzed with a specifically designed system equipped with ML approaches or deep learning methods such as CNNs. However, all of previous studies related to automatic petrographic analysis are restricted by the insufficiency of the training data. As strengthed by the paucity of large volume of well-labeled data significantly impeded the development of novel deep learning methods. In this context, the main motivation of this thesis is to close this data gap by building a consistent and sufficiently large training dataset that can be used to develop advanced ML- and DL-based applications for petrographic identification.

- 2001 — (Thompson et al., 2001) Rock-forming minerals identification using three-layer ANN trained with a small manual created dataset
- 2005 — (Marmo et al., 2005) Textural identification of marine carbonate using three-layered ANN
- 2010 — (Singh et al., 2010) Textural identification of basaltic rock using three-layered ANN
- (Baykan & Yılmaz, 2010) Identification of limited types of minerals using three-layer ANN based on images showing the maximum intensity values.
- 2013 — (Młynarczuk et al., 2013) Classification of rock thin section images under static lighting and polarisation using pattern recognition approaches
- (Ślipek & Młynarczuk, 2013) Classification of rock thin section images under changing lighting and polarisation conditions using pattern recognition approaches
- 2017 — (Budennyy et al., 2017) Sandstone grain segmentation and cleavage identification using a semi-automatic approach based on image processing and random forest.
- (Li et al., 2017) Interregional sandstone classification using a transfer learning model.
- (Jiang et al., 2017) Quartz grain boundaries are extracted multi-angle thin section microscopic images.
- (Cheng & Guo, 2017) Granularity analysis using CNN
- (Tang & Spikes, 2017) Image segmentation of scanning electron microscopy (SEM) images of shale using CNN
- 2018 — (Ramil et al., 2018) Granite-forming minerals identification using three-layer ANN
- 2019 — (Iglesias et al., 2019) Differentiation between the mounting resin and quartz phase in the images of iron ore using CNN
- (Borges & de Aguiar, 2019) Mineral identification for rock microscopic images taken under different polarisation modes using decision tree and nearest neighborhood
- (Ye Zhang et al., 2019) Rock mineral identification using ML model stacking. High-level features of quartz and feldspar in the microscopic images are extracted using a transfer learning model based on a previously trained deep learning model
- (Karimpouli & Tahmasebi, 2019) Image segmentation of scanning electron microscopy (SEM) images of sandstone using CNN

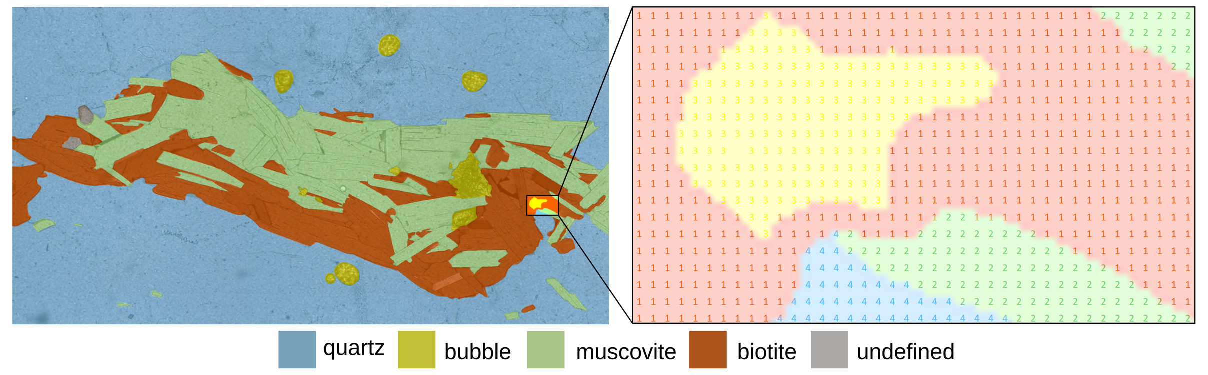
Fig.1. Timeline of ML and deep learning-based approaches for petrographic analysis. The drawbacks existing in the research are marked with different color-coded dots. small training dataset, insufficient data, closed dataset, low generalization capacity, feature engineering, images are taken under static lighting and polarisations, information loss in the dataset.

ViP Data Set



The raw data set is generated by virtual petrographic microscopy (ViP), a cutting-edge methodology that can automatically scan entire thin section in gigapixel resolution. The scanning process is performed sequentially along a predefined grid and repeated for different rotation angles of crossed polarizers. The scanned mosaic image can be precisely overlapped which allows to interpolate and to fit the extinction behavior of each individual pixel as a smooth function. Based on the interpolated extinction information, a phase map qualitatively showing the mineral axis misorientations can be produced. Extra complementary image layers reflecting chemical and physical information of the thin section can be stacked along the third axis to the image cube.

Image Annotation



Thin section images encompass tons of local and contextual information, only pixel-wise labeling can sufficiently cope with the complexity widely existing in the image of thin sections. pixel-wise annotation assigns each pixel with a class label. Each class represents one type of mineral and is indicated by a unique color mode. The output of pixel-wise labeling (semantic labeling) would be an integer mask with the same size as the input image.

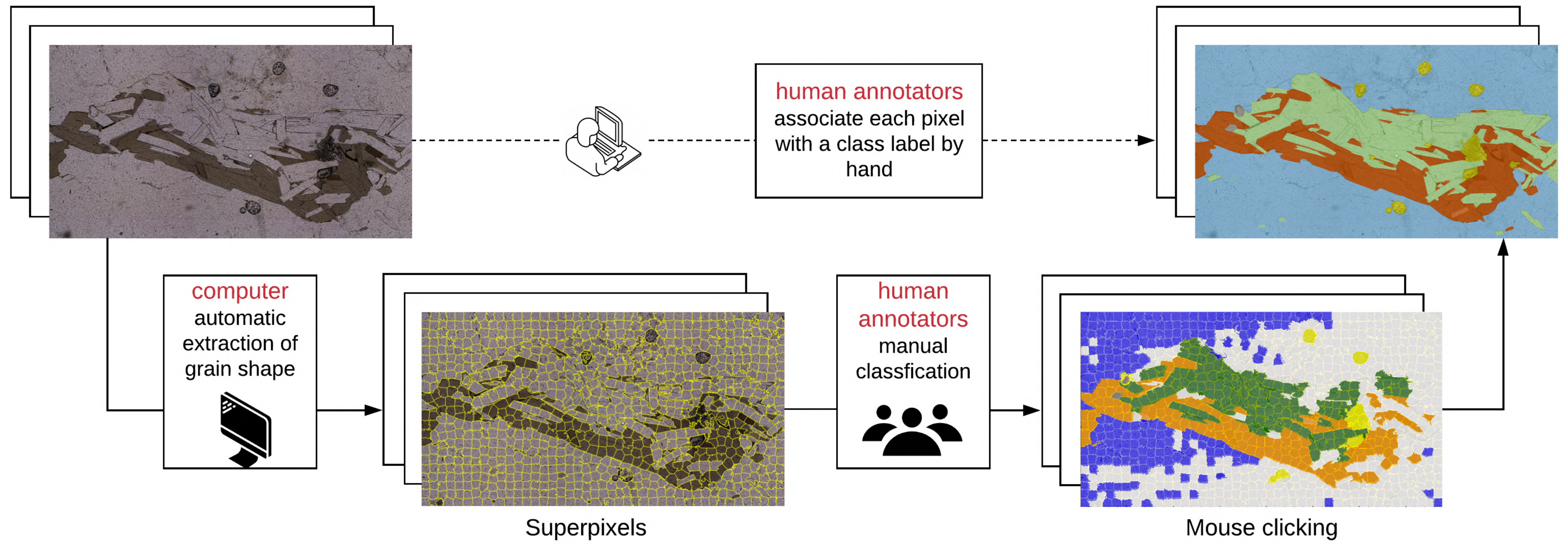
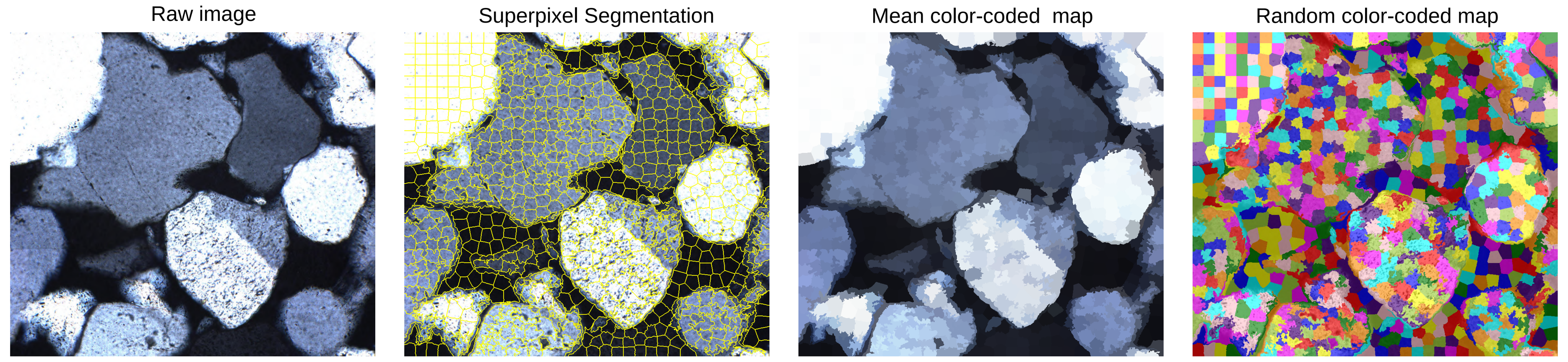


Image annotation, especially pixel-wise annotation is always time-consuming and inefficient. Moreover, it would be particularly challenging when to manually create dense semantic labels for ViP data in view of its size and dimensionality.To address this problem, we proposed a human-computer collaborative annotation pipeline where computers extract image boundaries by splitting images into superpixels, while human-annotators subsequently associate each superpixel manually with a class label with a single mouse click or brush stroke. This frees the human annotator from the burden of painstakingly delineating the exact boundaries of grains and it has the potential to significantly speed up the annotation process.



Pixels are rectangular basic units of images, whereas Superpixels (SPs) are a group of pixels that are perceptually similar. Instead of providing a discrete representation of images, superpixels are better aligned with image edges and largely reduce the image complexity. Unlike object segmentation that aims to find hard decisions about the outline of the object, superpixels generate a controlled oversegmentation of images from which the shape of grains can be recovered in the subsequent processing. Usually, if K represents the number of objects in the image, P = m x n is the number of pixels of the input image where m, n is the height and width [px] of the given image, then for the number of superpixels N:

K<<N<<P

Superpixel Benchmarks

Given an image *I* having *N* pixels, $S = \{S_1, \cdots, S_m\}$ is superpixel segmentation, $G = \{G_1, \cdots, G_n\}$ is ground truth segmentation, metrics are defined as:

- **Boundary Recall** assessed how well the superpixel boundaries aligned with the ground-truth edges

$$Rec(G,S) = \frac{TP(G,S)}{TP(G,S) + FN(G,S)}$$

- **Compactness** mesures the similarity of a single supepixel to a circle

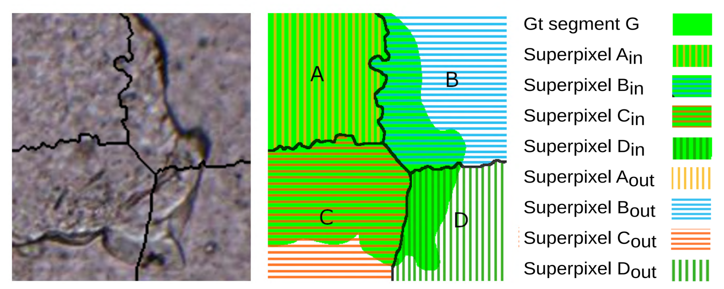
$$CO(G,S) = \frac{1}{N}\sum_{S_j} |S_j| \frac{4\pi A(S_j)}{P(S_j)}$$

- **Explained Variation** provides a human-independent quantification

$$EV(S) = \frac{\sum_{S_j} |S_j| (\mu(S_j) - \mu(I))^2}{\sum_{x_n} (I(x_n) - \mu(I))^2}$$

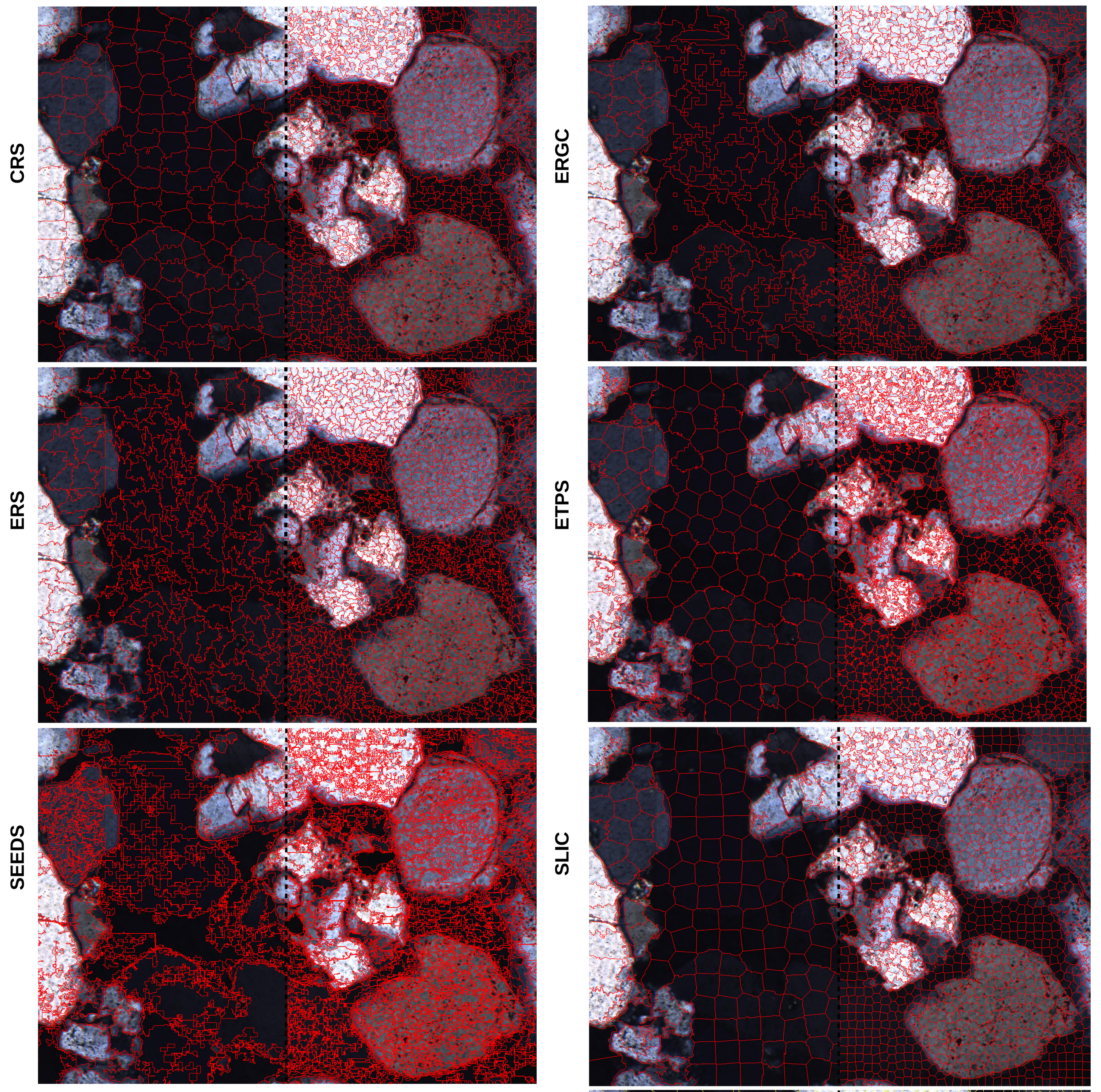
- **Undersegmentation Error** measures the total amount of superpixel leak with respect to the ground-truth segment border

$$UE(G,S) = \frac{1}{N}\sum_{G_i}\sum_{S_j \cap G_j \neq \varnothing} \min\{|S_j \cap G_i|, |S_j - G_i|\}$$

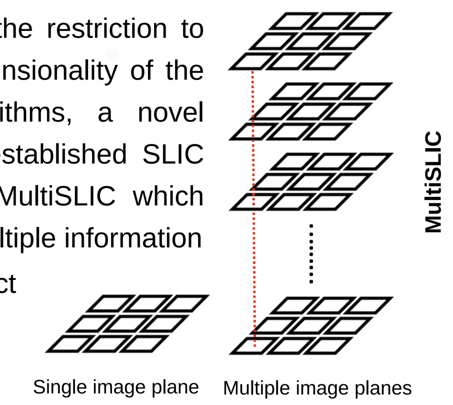


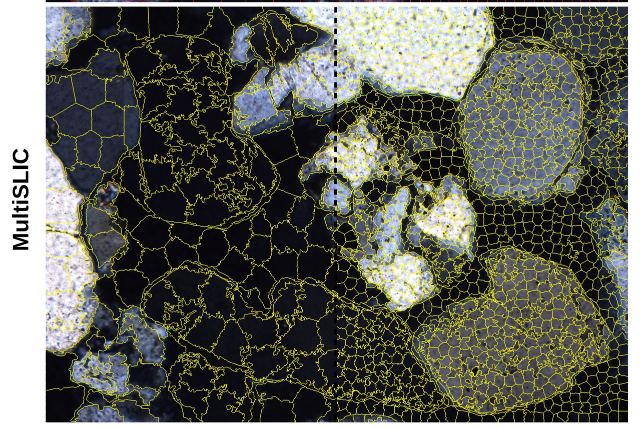
$$UE\_{Neubert} = (|A_{out}| + |B_{in}| + |C_{out}| + |D_{in}|)/|G|$$

Superpixel Evaluation

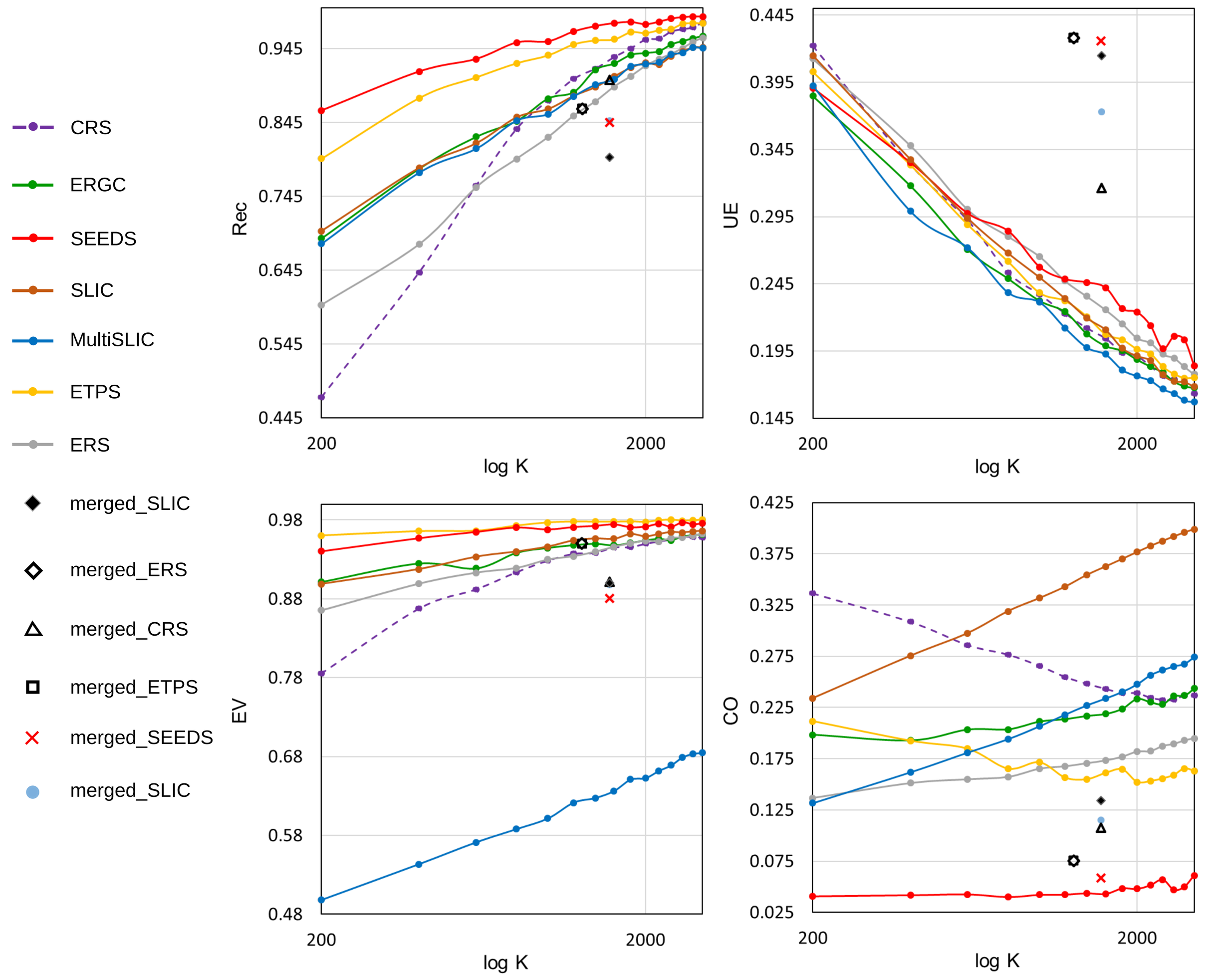


Motivated by the restriction to the input dimensionality of the existing algorithms, a novel adaption for established SLIC is proposed: MultiSLIC which can take in multiple information layers to extract superpixels

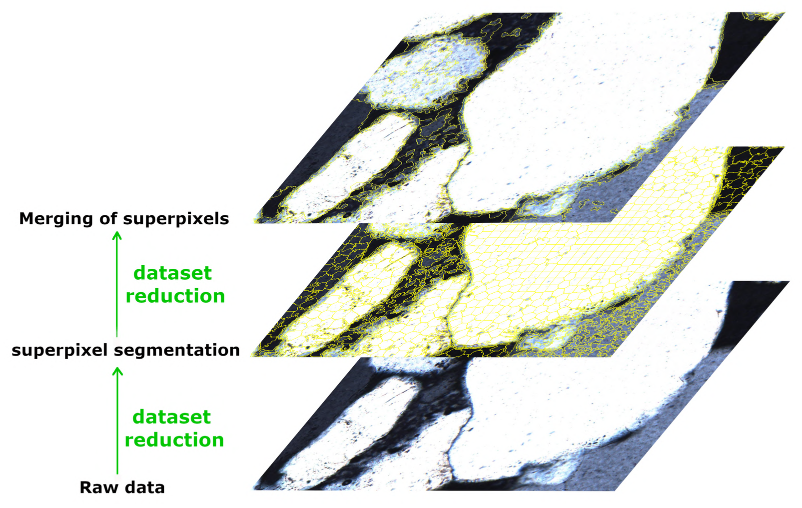




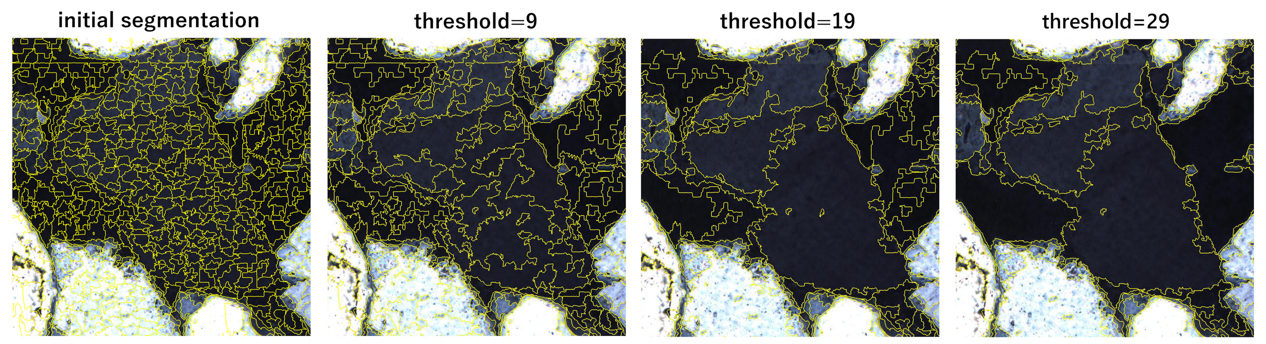
The performances of tested algorithms are compared with respect to *Rec*, *UE*, *EV* and *CO*. Ideal approach to be used in the annotation pipeline should have excellent boundary adherence with low boundary leakage, therefore, Rec and UE are given prior attention. The existing results demonstrate that ETPS and SEEDS are considerably better performing than others in many aspects. ETPS also makes a good trade-off between the compactness of superpixels and boundary adherence. Although MultiSLIC shows advantages in detecting the region boundaries for small *K*, it cannot compete with SEEDS and ETPS for *K*=3000. On the other hand, merged superpixel segmentation provides less redundant representation for original images than initial superpixel segmentation, but quantitatively, the boundary recall of merged segmentation is largely reduced compared to the one that is not merged.



Superpixel Merging



The idea of merging superpixels came from the observation that the initial superpixel segmentation still includes redundancy that could be captured. The classical way to simplify the initial segmentation is to merge adjacent regions based on color similarity and spatial proximity. Merging of superpixels produce a coarser segmentation while still retaining the important boundaries of images



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*Presenting Author yujiaxin666@outlook.com

Affiliation

[1] RWTH-Aachen, Geoscience, Department of Computational Geoscience and Reservoir Engineering, Germany
[2] RWTH-Aachen, Lehr- und Forschungsgebiet für Geologie-Endogene Dynamik, Germany
[3] RWTH-Aachen, Visual Computing Institute, Computer Vision Group, Germany
[4] Microstructure and Pores GmbH, Germany