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ON THE RELEVANCE OF SEGMENTATION IN THE CASE OF POOR CONTRAST

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1. Introduction

Segmentation enables to partition the image into regions so that each region is homogeneous with regard to certain properties, such as gray level or texture. Each phase constituting the sample is associated to a gray level depending on its X-ray attenuation coefficient. When the attenuation contrast is poor, the peaks in the gray level histogram, corresponding to the different material phases, overlap and render segmentation difficult. In this context, we have compared different segmentation strategies and quantified their potential to discriminate each phase.

2. Materials and Methods

For this study, we use a sample from a natural aquifer dedicated to CO_2 storage and constituted of 3 phases: deposits and grains (quartz and calcite) saturated by water. The grains present good contrast with respect to the two other phases. However, water and deposits have similar X-ray attenuation coefficients, making their discrimination very difficult (fig 1a). The sample was scanned with a Zeiss Xradia Versa 510 tomograph at 40 kVp to optimize the absorption contrast. The voxel size is 2.5 microns. Four different segmentation strategies are tested in order to extract the 3 phases, namely Otsu thresholding, K-means thresholding (KM), Histographic segmentation (HS) and Machine learning segmentation (ML). All these methods are available in ORS Dragonfly, which is the tool used for our analyses.

In order to compare quantitatively and spatially the results, a representative image has been extracted from the data set, segmented manually and the result is considered as the reference segmentation S_{ref}. Next, a classifier C_i is calculated by computing $C_i = 2S_{ref,i} - S_i$, where S_i is the segmented image by any of the four other considered methods, and the index i refers to one of the three phases. The classifier image can yield 4 distinct values, enabling whether a pixel is only segmented in the reference, only in the considered segmentation method, or identified by both of none of them. In addition, the volume fractions of each phase have been determined on the whole scanned volume and analyzed.

3. Results and Conclusions

For the predominant and easy to segment grain phase, all methods do a good job. However, most methods overestimate the water-phase and correspondingly underestimate the amount of deposits (table 1). Only Machine Learning has a consistent performance with similar errors for each phase. The corresponding segmentation is shown on figure 1b. The large errors (near 50%) on the smallest phase (deposits) highlight that segmentation should be done with care in low-contrast cases.

	Ref.	False negatives				False positives			
	(%)	Otsu	KM	HS	**ML**	Otsu	KM	HS	**ML**
grain	61.5	0.6	1.2	1.6	**0.4**	1.3	0.0	1.0	**0.6**
H_2O	28.4	0.0	0.0	0.3	**0.5**	4.4	4.6	4.1	**0.3**
deposit	10.1	4.9	3.5	3.8	**0.8**	0.3	0.7	1.0	**0.8**

Table 1: Key results of the segmentation study.

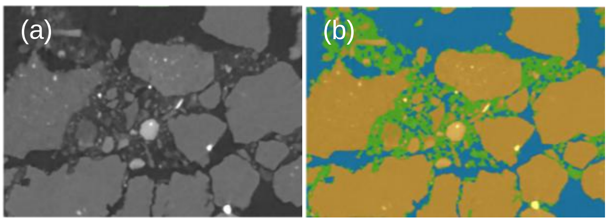

Fig 1: Original (a) and segmented (b) slice showing grains (yellow), water (blue) and deposits (green).

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