Modelling intensity and gradient distribution of 3D tomography data for direct extraction of physical parameters and robust evaluation of segmentation

Elise O. Brenne *[1], Vedrana A. Dahl [2], and Peter S. Jørgensen [1]

[1]Department of Energy Conversion and Storage, Technical University of Denmark, Denmark
[2]Department of Applied Mathematics and Computer Science, Technical University of Denmark, Denmark

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Summary: We propose a novel intensity distribution model for material interfaces. Intensity gradient information is exploited for robust model fitting. Our model allows for direct extraction of physical sample parameters, assists segmentation, and provides a methodology for evaluating segmentation results.

1. INTRODUCTION

3D tomography is a powerful tool for understanding complex structure-property relations in material science [1]. A typical workflow includes acquisition of projection data, 3D tomographic reconstruction and segmentation, followed by estimation of structural parameters or simulation of physical processes using geometries from the segmented data. The accuracy of the extracted material parameters is thus directly dependent on the quality of the segmentation.

This reliance on the segmentation raises a number of issues. One major issue relates to the assessment of the segmentation quality. Currently, many segmentation methods are to a high degree reliant on visual inspection for parameter tuning, relying on what appears to be correct in the eyes of the operator [2]. This makes it challenging for others to reproduce measurements, assess the validity of the segmentation and assess the uncertainty in the extracted material parameters. Moreover, with the increasing interest in *in situ* time series measurements, huge amounts of 3D image data are generated. Manual assessment of the quality of the image segmentation is becoming infeasible.

2. METHODOLOGY

To address these issues, we propose to support the segmentation by explicitly modelling the distribution of voxel intensities in the data based on physical parameters of the material and image capturing process. This concept is already exploited in Gaussian mixture models where the phase fractions, mean intensity levels for each phase and noise level are modelled as the weight, mean and variance of several Gaussian components [3]. The main shortcoming of this model is that it does not account for the interfaces between materials, which often appear blurry as a result of finite resolution in the imaging system.

Our model is an extended mixture model that also accounts for the interfaces between materials. The model makes use of information about the intensity of neighboring voxels through the gradient magnitude calculated by central differences. The joint probability density function (PDF) of the intensity/intensity gradient magnitude distribution is derived, assuming additive Gaussian noise. Figure 1 exemplifies how interfaces between materials influence a joint intensity/intensity gradient magnitude histogram. In the 1D histogram, the regions with voxels from the interfaces and from the phase interiors overlap, while in the 2D histogram, they are clearly separated. It is this distinct structure our model exploits to make robust model fitting feasible. The model parameters are estimated using maximum likelihood estimation.

*e-mail: elbre@dtu.dk

The fitted model has several promising perspectives. Firstly, physical information like interface resolution, noise level, phase interior intensities and volume fractions are parameters of our model. Through fitting the model to the tomography data, these parameters are determined directly and thus provide a consistency check when compared to the same parameters obtained through segmentation and prior information. Exploiting this in a workflow involving automatic segmentation of large datasets would provide a simple check of how well the segmentation method is performing, provide a means of detecting whether something goes wrong from a lack of model fit and remove the reliance on visual inspection.

The fitted model provides excellent input data for use in existing probabilistic segmentation methods (see e.g. [4]). For a material containing three phases, the join probability distribution derived from our model gives a probability for each voxel to belong to each of six classes - the interior of each class as well as the three types of interface. Voxel classification can then be done based on these probabilities rather than the raw intensity data.

3. RESULTS

Early results show that our model is currently outperforming the traditional Gaussian mixture model on artificial 3D image data containing blurred interfaces and homogeneous phase interiors with Gaussian noise. We present details on how the interface distribution is modeled, how it can be fitted to new data and how the model can be exploited, with examples on artificial and experimentally obtained 3D image data.

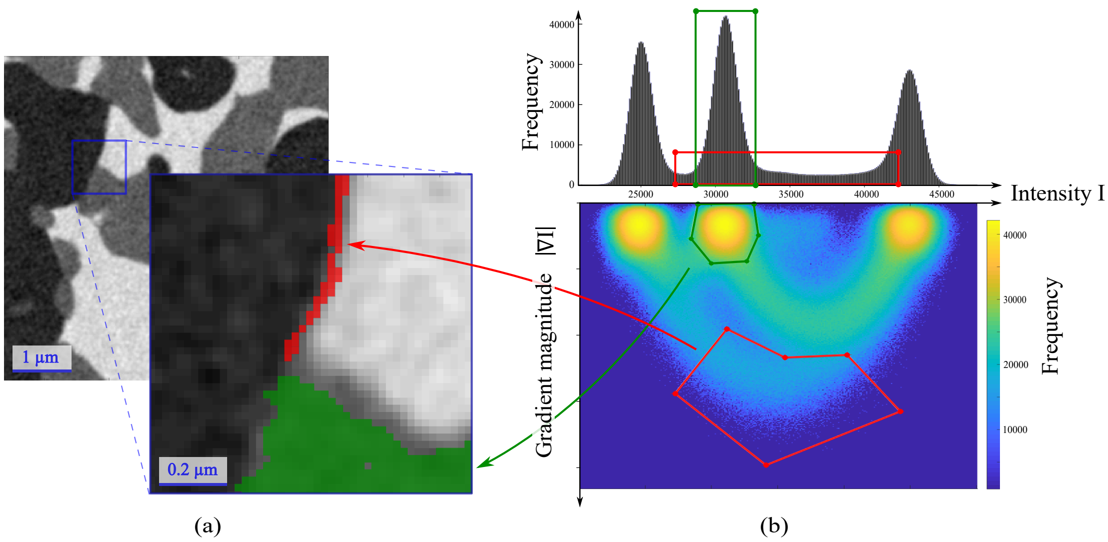

Figure 1: (a) 3D x-ray data of a solid oxide cell electrode [5]. Inset: zoomed-in region with color overlay. (b) 1D intensity histogram (top) and 2D intensity-gradient histogram (bottom) of the fuel cell data. Intensities corresponding to the interior of each of the three material phases are seen as three characteristic peaks in the 1D histogram, and as three blobs in the 2D histogram. The regions indicated with green and red map to the voxels of the same color in the inset. In the 1D histogram, the regions overlap, while in the 2D histogram, the regions are clearly separated.

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