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Unsupervised multi class segmentation of 3D images with intensity inhomogeneities ☆

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ABSTRACT

Intensity inhomogeneities in images cause problems in gray-value based image segmentation since the varying intensity often dominates over gray-value differences of the image structures. In this paper we propose a novel biconvex variational model that includes the intensity inhomogeneities to tackle this task. We combine a total variation approach for multi class segmentation with a multiplicative model to handle the inhomogeneities. In our model we assume that the image intensity is the product of a smoothly varying part and a component which resembles important image structures such as edges. Therefore, we penalize in addition to the total variation of the label assignment matrix a quadratic difference term to cope with the smoothly varying factor. A critical point of the resulting biconvex functional is computed by a modified proximal alternating linearized minimization method (PALM). We show that the assumptions for the convergence of the algorithm are fulfilled. Various numerical examples demonstrate the very good performance of our method. Particular attention is paid to the segmentation of 3D FIB tomographical images serving as a motivation for our work.

1. Introduction

Intensity inhomogeneities often occur in real-world images mainly due to different spatial lighting and deficiencies of imaging devices. For example in MRI, imperfections in the radio-frequency coils or problems associated with acquisition sequences cause intensity changes. The motivation for this paper was the task of segmenting 3D images stemming from focused ion beam (FIB) tomography. While classical X-ray tomography does often not reach the required material resolution, FIB tomography enables to investigate the 3D morphology of structures on a scale down to several nanometers. The material is successively removed by a focused ion beam and after every section, the surface is displayed by scanning electron microscopy. Several hundred of these serial slices finally form a 3D image. A typical slice of a 3D FIB tomography of aluminum with silicon carbide (SiC) particles (larger black parts) and copper aggregations (small white parts) is shown in Fig. 1(a). The segmentation has to distinguish between the particles, the aggregates and the surrounding aluminum matrix. However, due to the intensity inhomogeneities, a segmentation based on the gray-values gives a very bad result. Fig. 1(a) and (c) shows segmentation results for a 3D FIB data set using a supervised gray-value based segmentation method without considering the illumination. Therefore, we have to choose one cluster center for each of the three classes, i.e., in total three gray-values that are close to the classes aluminum, SiC and copper, respectively. Unfortunately, the cluster centers cannot be chosen appropriate for all parts of the image so that either too many or not enough particles are detected. Therefore the segmentation of such images has to take the intensity inhomogeneities into account.

There are several techniques for illumination corrections in the literature. These methods could be used in a preprocessing step before applying a segmentation algorithm of choice. In particular in MRI, intensity corrections were proposed by simple homomorphic filtering [12,21] and polynomial, resp., spline surface fitting approaches [16,31,42,17]. Many spatial illumination correction methods for natural images take hypotheses about the Human Visual System (HVS) into account. In particular, the perceptual work about the Retinex model [22] has found wide acceptance. It states that the HVS does not perceive an absolute lightness but rather a relative, local one. This phenomenon is called lateral inhibition. For example, Fig. 2 shows the experiment of the checkerboard shadow illusion of Adelson [1]. Although the squares A and

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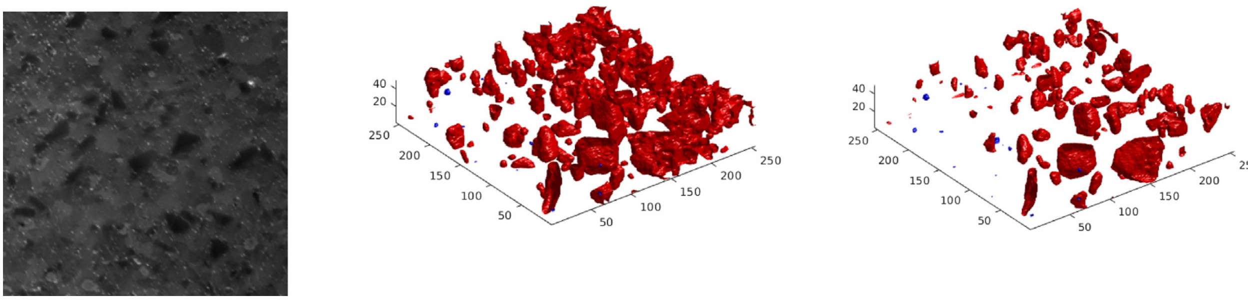
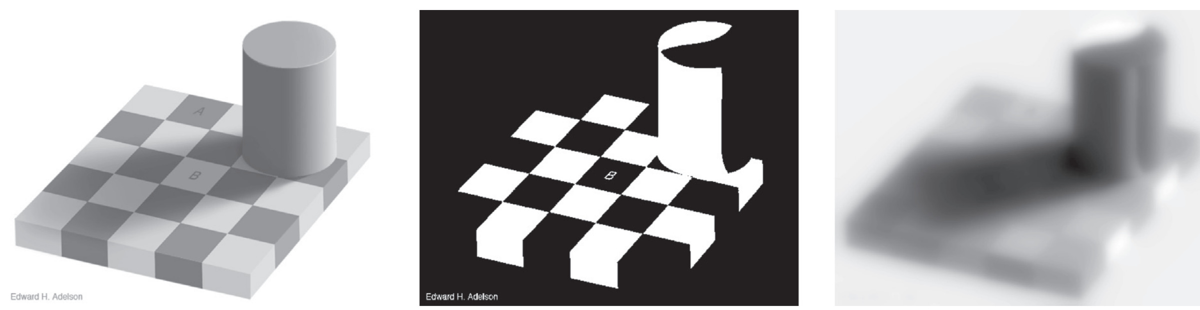


(a) Exemplary slice of a 3D data set with intensity inhomogeneities

(b) Segmentation without considering intensity inhomogeneities with cluster centers chosen such that the left part is segmented correctly, but there are too many particles segmented in the right part.

(c) Segmentation without considering intensity inhomogeneities with cluster centers chosen such that the right part is segmented correctly, but there are too few particles segmented in the left part.

Fig. 1. One slice of FIB data with varying illumination and two 3D segmentation results using a model not considering the illumination.



(a) Original image (b) Segmentation result (c) Computed illumination

Fig. 2. Result for the "checkerboard" image.

B have the same gray-value, the perceived intensities are different. In the Retinex model, the light intensity F perceived by the observer or camera is considered to be the product of the reflectance of the objects R in the scene and the amount of source illumination L falling on the objects, see also [18, p. 51],

$$F(x) = R(x)L(x), \qquad (1)$$

where $R(x) \in (0,1)$ and $L(x) \in (0,+\infty)$. While we assume that the reflectance inherits the structures of the objects, e.g. edges, we consider the illumination as spatially smooth, in particular it should not have sharp edges, which represent the image structures. Taking the logarithm in (1) we obtain

$$f(x) = r(x) + l(x),$$

where $f = \log F, r = \log R$ and $l = \log L$. Retinex based variational or PDE based approaches for illumination corrections can be found for example in [28,30,33,34].

In MRI the observed intensity is often modeled similarly as in (1) by the product of a structural part R and a so called gain factor L. In this paper we also follow the multiplicative intensity model.

In contrast to a two step procedure we consider the simultaneous segmentation and intensity inhomogeneity estimation. This avoids the computational burden of two separate procedures and has moreover the advantage of being able to use intermediate information from the segmentation while performing the update. Besides statistical methods as the computationally extensive EM approach in [43], variational based algorithms were proposed in [2,3,25,26,29,36,45]. We consider the later approaches in more detail in the next section.

Variational segmentation models have shown a very good performance and flexibility in many applications. Level set methods and convex segmentation models which penalize the (nonlocal) discrete total variation (TV) of a relaxed label assignment matrix have been successfully applied [5,11,15,23,24,37,40,44].

In this paper, we combine the TV based segmentation method with the multiplicative intensity model. This results in a biconvex non smooth functional, which has to be optimized with respect to the label assignment matrix, the cluster centers and the smoothly varying intensity factor. Then we obtain both a segmented image and an estimation of the intensity inhomogeneities. We compute a critical point of the corresponding functional by applying a slight modification of the proximal alternating linearized minimization method (PALM) by Bolte et al. [10].

The paper is organized as follows: In Section 2 we review variational segmentation models which compensate for the varying intensities while segmenting the image. Then we introduce our model. The modified PALM is explained in Section 3. Section 4 contains numerical examples. The paper finishes with conclusions in Section 5.

2. New model

Let $\mathcal{G} := \{1,\ldots,n_1\} \times \ldots \times \{1,\ldots,n_d\}$ be a d-dimensional image grid. Here we will deal with $d = 2$ and $d = 3$. Let $n = n_1 \ldots n_d$ be the number of image pixels. We consider images $F : \mathcal{G} \to \mathbb{R}$ which we want to segment into K classes. We introduce a so-called label assignment matrix

$$u := (u_k(j))_{j\in\mathcal{G},k\in\{1,\ldots,K\}}.$$