De-noising of SRμCT Fiber Images by Total Variation Minimization

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***Abstract*—SRμCT images of paper and pulp fiber materials are characterized by a low signal to noise ratio. De-noising is therefore a common preprocessing step before segmentation into fiber and background components. We suggest a de-noising method based on total variation minimization using a modified Spectral Conjugate Gradient algorithm. Quantitative evaluation performed on synthetic 3D data and qualitative evaluation on real 3D paper fiber data confirm appropriateness of the suggested method for the particular application.**

I. INTRODUCTION

Paper is a material constituted mainly of a network of cellulose fibers whose diameter and length are about 40 μm and 2 mm, respectively. Due to its wide presence in everyday life it is of interest to study and properly utilize its properties. A lot can be concluded about the macroscopic properties of paper based on the microscopic 3D structure of the material.

Synchrotron radiation X-ray microtomography (SRμCT) is an imaging technique that provides access to three-dimensional information at a high spatial resolution. The intensity of each image element in a SRμCT image corresponds roughly to the density of the material it represents. Binarization of the image into two disjunct components – fiber and background, is in most cases required before further measurements of the microscopic properties can be made. However, due to the very low density difference between pulp fiber and the surrounding void, the image contrast and the signal to noise ratio are rather low. To reduce the impact of image artifacts and noise, various pre-processing steps and de-noising filtering methods are commonly applied before the binarization step. However, studies show that none of the commonly used de-noising methods performs ideally, and that there is still room for improvements.

Recent results in image de-noising based on minimization of an appropriately defined energy functional motivated the research presented in this paper. The method we suggest for improved de-noising of 3D microtomographic images of wood fiber materials is based on total variation (TV) minimization by using a modified spectral conjugate gradient (SCG) method. Our recent studies of the suggested de-noising method, [1], have confirmed its very good performance. The tests carried out and presented in this paper confirm its appropriateness for the particular task of de-noising SRμCT fiber images. Evaluation is performed on synthetic data, enabling ground truth information, as well as on real data. Both quantitative evaluation, performed by computing normalized mutual information (NMI), when synthetic data is used as ground truth, and visual inspection, in case of tests on real images, show that the suggested de-noising method gives better results than, so far most commonly used, SUSAN filtering.

II. BACKGROUND

De-noising of SRμCT fiber images is analyzed in a number of publications by now, [2]–[4]. A common important property of the suggested methods is that smoothing is performed so that sharp edges and small details in the image are preserved.

Bilateral filtering [5] combines information from image elements that are close both spatially and in terms of intensity. Such a filter is a product of a domain and a range filter. Gaussian functions are often used to weight both spatial closeness and intensity similarity.

3D SUSAN smoothing [6] is an approach similar to bilateral filtering, with two main differences: (i) the central element is not included in the calculation of the value to be assigned to the observed point, and (ii) median filter is applied when the filter value is considered unreliable. It is expected that impulse noise is more efficiently reduced due to these modifications.

Anisotropic diffusion [7] is a method which provides iteratively smoothed images by approximating a diffusion process. Based on the local content of the image, the diffusion coefficient is chosen to vary spatially in such a way as to encourage intraregion smoothing in preference to interregion smoothing.

Performance of these three edge-preserving smoothing methods when applied to 3D SRμCT fiber images is studied in [8]. It is concluded that SUSAN smoothing outperforms bilateral filtering, whereas anisotropic diffusion has a slight advantages over SUSAN regarding edge preservation, however, with a less good handling of individual noise voxels. A similar result is observed in [9], where it is concluded that anisotropic diffusion and SUSAN smoothing give equally good results, with SUSAN being significantly faster.

1051-4651/10 $26.00 © 2010 IEEE
DOI 10.1109/ICPR.2010.1116

III. De-noising by energy minimization

The method that we suggest for image de-noising belongs to the family of energy function minimization approaches. The energy function observed is a simplification of the Mumford-Shah functional [10]:

$$J(u) = \int_{\Omega} \varphi(|\nabla(u)|)\, d\mathbf{V} + \frac{\mu}{2} \int_{\Omega} (u-g)^2\, d\mathbf{V}\ , \quad (1)$$

where g and u are the observed and smoothed image, respectively, $\nabla(u)$ is the image gradient, and Ω is the (continuous) image domain. The first term (regularization term) of (1) uses information about local intensity variation and, for an appropriately chosen potential function φ, smooths regions with low intensity variation, while preserves high variation of intensities where such appear. The second term (data fidelity term), ensures image data preservation. The positive parameter μ controls the balance between these two term.

Minimization of the above energy function is non-trivial, and several optimization methods have been proposed in the literature for that purpose. Our recent studies, [1], show that the Spectral Conjugate Gradient optimization strategy performs very well for minimization of (1), leading to a fast and very flexible de-noising method. In this paper, we present results of de-noising SRμCT fiber images by minimization of (1) by the modified SCG strategy suggested in [1].

We use the following differentiable discretized version of the functional (1) in the numerical optimization:

$$E(u) = \sum_{i=1}^{N} \varphi(\sqrt{|\nabla(u_i)|^2 + \varepsilon}) + \frac{\mu}{2} \sum_{i=1}^{N} (u_i - g_i)^2 \quad (2)$$

where $\nabla(u_i)$ is the discrete image gradient at a point u_i and ε is a small positive number. The minimization of (2) is performed using the method presented in [1]. The parameters of the process are selected according to the same study: $M = 1$, $\theta_{\min} = 10^{-3}$, $\theta_{\max} = 10^3$, $\gamma = 10^{-4}$, $\sigma_1 = 0.1$, $\sigma_2 = 0.9$, $Tol = 10^{-3}$, $\varepsilon = 10^{-5}$.

We perform tests using a number of different potential functions φ (see [1]). For each potential function, a range of values for the parameter μ is evaluated.

IV. Experiments and evaluation

We evaluate the performance of the proposed approach for de-noising of SRμCT fiber volumes and compare it with SUSAN filtering.

By now, qualitative – visual – evaluation has been mostly used, [2], [8]. However, it is very difficult to visually judge the quality of the 3D SRμCT volumes, and such evaluation is bound to be both subjective and error prone. For a more objective, quantitative evaluation, it is natural to try to compare the result with some ground truth. However, neither physical phantoms, nor reliable segmentation of the acquired images are easily available; mostly due to the poor image contrast, manual segmentation of the data is both difficult and subjective.

A big step towards reliable quantitative evaluation of SRμCT fiber volumes is made by a recent work presented in [11], where a generator of synthetic micro-CT images of wood fiber materials is proposed. This method provides images which are corrupted by several types of simulated noise and artifacts, while the correct composition of every image voxel is still available. The quantitative evaluation of the de-noising method suggested in this paper is based partly on experiments on synthetic image data generated following [11].

Even when the true material composition of every voxel is known, it is not trivial to design a suitable quantitative evaluation. The goal of the de-noising is to provide a good starting image for the following segmentation. Such an image is not necessarily similar to the correctly segmented image and a direct image comparison does not provide a fair performance judgment.

We suggest to use Normalized Mutual Information (NMI) to quantitatively evaluate de-nosing performance. This measure reflects information consistency between two images. The information contained in the correct segmentation should also be present in the de-noised image, despite not necessarily having similar gray levels. A high NMI value corresponds to a small spread (low entropy) of the joint histogram. NMI is computed as

$$NMI_n(A,B) = \frac{\sum_{i=1}^{n} H_A(i)\log H_A(i) + \sum_{i=1}^{n} H_B(i)\log H_B(i)}{\sum_{i=1}^{n}\sum_{j=1}^{n} H_{AB}(i,j)\log H_{AB}(i,j)}\ , \quad (3)$$

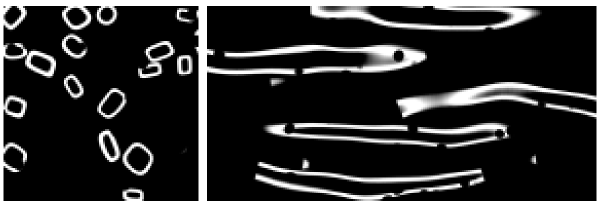
where H_{AB} is the joint histogram of A and B, H_A and H_B their marginal histograms respectively, and n is the number of histogram bins. The maximal $NMI = 2$ is reached when there is a one-to-one mapping between the gray levels of images A and B. The number of bins used in the histograms affect the result, see Table I.

Synthetic Data: A $200 \times 100 \times 100$ noise free synthetic fiber volume V is generated according to [11]. The volume is then degraded by image noise mimicking the image acquisition process, giving the observed volume O. The observed image O is de-noised, using the proposed energy minimization based method, leading to filtered image F_{TV}, as well as by SUSAN based filtering, providing filtered image F_{SUSAN}.

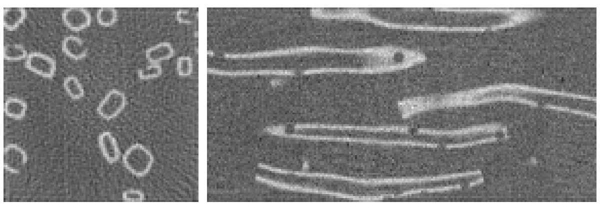
A range of settings are evaluated for the most important parameters of the respective methods, i.e., the function φ and parameter μ for the energy minimization, and σ and t for SUSAN filtering. $NMI_n(V, F_{\text{TV}})$ and $NMI_n(V, F_{\text{SUSAN}})$ are computed and the best performing parameter combinations are chosen. We have evaluated the potential functions listed

Table I
TV MINIMIZATION AND SUSAN BASED DE-NOISING OF SYNTHETIC DATA.

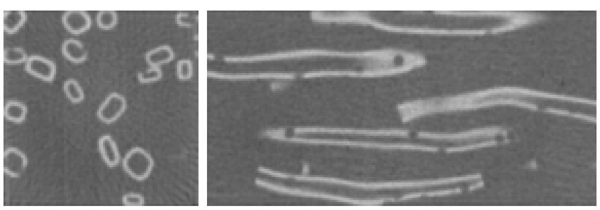
Method	Parameters	NMI_{64}	NMI_{256}	CPU-time
TV-SCG	$\mu = 31$	1.1799	1.1204	114s
SUSAN	$\sigma = 0.7$, $t = 180$	1.1728	1.1194	2s



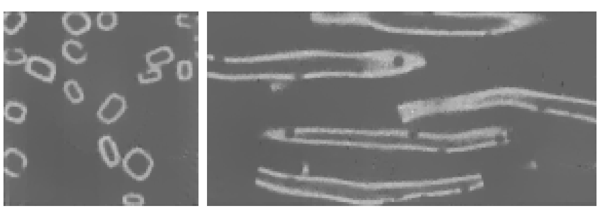
(a) Two perpendicular slices through the ground truth synthetic data



(b) Noisy "observed" synthetic data



(c) SUSAN filtered data with $\sigma = 0.7$ and $t = 180$



(d) TV-SCG filtered data with $\mu = 31$

Figure 1. SUSAN and TV-SCG based de-noising of synthetic data.

in [1] and we conclude that, for the observed images, the best performing one is the identity function. For this special case, when $\varphi(x) = x$, the minimization of (1) becomes Total Variation minimization.

The resulting NMI scores, with corresponding parameters, are presented in Table I, indicating a performance improvement by the proposed method. Note that the very small difference in NMI values still correspond to a significant change in image appearance (see Fig. 1).

For a visual evaluation, the noise free V, observed O, SUSAN filtered F_{SUSAN}, and TV-filtered F_{TV} image volumes are observed. Two perpendicular slices through each volume are shown in Fig. 1. Histograms of O, F_{SUSAN}, and F_{TV} are displayed in Fig. 2.

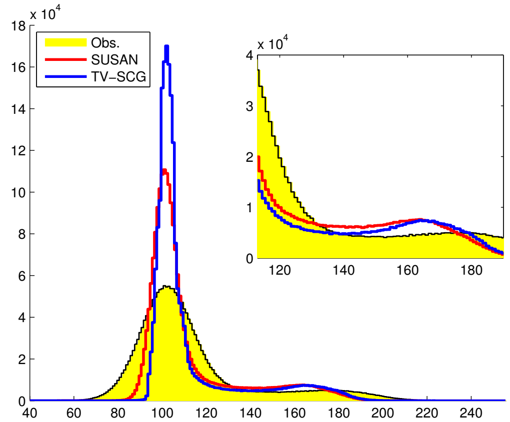
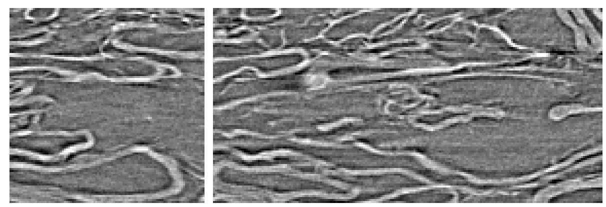
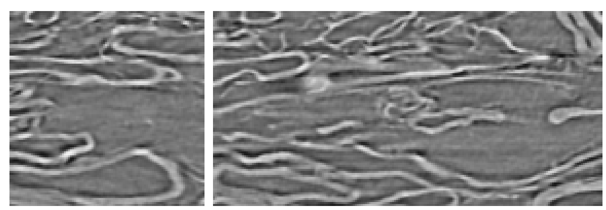


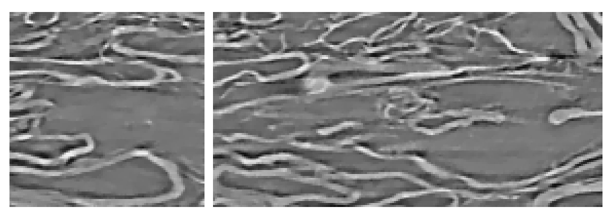
Figure 2. Histograms of the observed O, SUSAN filtered F_{SUSAN}, and TV-filtered F_{TV} synthetic image volumes.



(a) Two perpendicular slices through real SRμCT data



(b) SUSAN filtered data with $\sigma = 0.7$ and $t = 180$



(c) TV-SCG filtered data, $\mu = 31$, 28 iterations, 60s

Figure 3. SUSAN and TV-SCG based de-noising of real SRμCT data

Real Data: SRμCT images of fibrous materials are acquired at the European Synchrotron Radiation Facility (ESRF) in Grenoble, at beam line ID19. A $200 \times 100 \times 100$ voxel region (approx. $140 \times 70 \times 70\mu$m) containing fibers of mechanically treated pulp is extracted and de-noised using SUSAN filtering and the proposed method. Slices through the image volumes are presented in Fig. 3 and histograms are shown in Fig. 4.

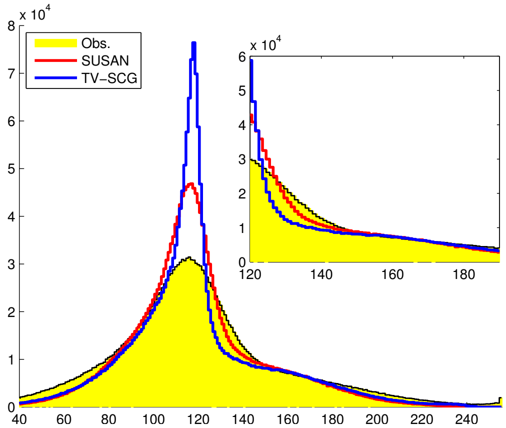


Figure 4. Histograms of real SRμCT data: Observed, SUSAN filtered, and TV-SCG filtered image volumes.

Visual inspection of the histograms of both synthetic and real data shows that the proposed method provides a more narrow background peak and fewer voxels in the gray region between clear background and clear foreground intensities, than the SUSAN filtering (see zoomed histogram regions). We interpret this as an indication that the proposed method provides a better starting point for subsequent segmentation.

V. Conclusions

We have addressed the problem of de-noising of 3D SRμCT paper fiber images. These images exhibit low contrast and are corrupted by noise, justifying the use of de-noising prior to further image processing. We suggest denosing based on Total Variation minimization. The minimization is realized using a modified Spectral Conjugate Gradient Algorithm. This particular method has shown good performance in our recent studies, [1].

We utilize the recently proposed method by Wernersson et al. [11] to generate synthetic data, enabling a quantitative evaluation based on Normalized Mutual Information. Comparison with, by now, mostly used SUSAN filtering method, on synthetic and real images, shows advantages of the proposed method, however at a cost of lower speed. Having on mind that the time required for image acquisition is often well over an hour, we feel that this is no major obstacle.

De-noising results of real images are visually inspected, both by observing 2D slices and image histograms. Being aware that visual inspection always is subjective, we still find it reasonable to conclude that the proposed de-noising method exhibits superior performance.

Acknowledgment

We are grateful to Erik Wernersson, Centre for Image Analysis, Uppsala, Sweden, for providing the synthetic image data. J. Lindblad and N. Sladoje are supported by the Ministry of Science of the Republic of Serbia through Projects ON144018 and ON144029 of MI-SANU.

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