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DECONVOLUTION REGULARIZED USING FUZZY C-MEANS ALGORITHM FOR BIOMEDICAL IMAGE DEBLURRING AND SEGMENTATION

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ABSTRACT
We address deconvolution and segmentation of blurry images. We propose to use Fuzzy C-Means (FCM) for regularizing Maximum Likelihood Expectation Maximization deconvolution approach. Regularization is performed by focusing the intensity of voxels around cluster centroids during deconvolution process. It is used to deconvolve extremely blurry images. It allows us retrieving sharp edges without impacting small structures. Thanks to FCM, by specifying the desired number of clusters, heterogeneities are taken into account and segmentation can be performed. Our method is evaluated on both simulated and Fluorescence Diffuse Optical Tomography biomedical blurry images. Results show our method is well designed for segmenting extremely blurry images, and outperforms the Total Variation regularization approach. Moreover, we demonstrate it is well suited for image quantification.

Index Terms— Deconvolution, segmentation, deblurring, regularization, Fuzzy C-Means, heterogeneity, quantification, molecular imaging

1. INTRODUCTION

In biomedical imaging, the blurring of images is often a problem for the segmentation and the quantification of the signal. To solve this problem, deconvolution is used [1]. Because deconvolution is an ill-posed problem, there is no consensus on this issue. In fluorescence imaging, the well-known Maximum Likelihood Expectation Maximization (MLEM) deconvolution method, is often used because it has the advantage to ensure non-negativity [2]. However, this iterative process has the drawback to converge to noise producing ringing artifacts. Convergence is ensured if regularization is implemented [1]. In biomedical imaging, Wavelet [3, 4] and Total Variation [5, 6, 7] are widely used for regularization. Multiscale wavelet-based approach reduces the noise in the residual using Bayeshrink filtering. Because of the multiscale approach, small structures can be preserved. However, contours are not sharp [4]. Total Variation enforces smoothness in the convolved data by adding a term based on spatial context (L1 or L2 norm) [5]. Using L1 norm, the advantage is that contours are sharp. The disadvantage is that small structures can be removed.

The Fuzzy C-Means (FCM) [8] clustering method is widely used for biomedical image segmentation. Derived from fuzzy logic [9], FCM is used to model imprecision by affecting to each voxel membership degrees according to multiple clusters. In [10], the authors propose to use FCM for dealing with heterogeneity in magnetic resonance images. In [11], a wavelet based approach is incorporated to the FCM algorithm in order to model heterogeneity using a multiscale approach in positron emission tomography images. In these two approaches, a spatial constraint is also added for noisy data regularization. Using FCM in imaging, incorporating neighborhood information is needed to improve voxel labeling. Although it can be easy to use neighborhood to remove noise, it is more difficult to remove blur corresponding to a lack of knowledge.

Methods combining both restoration and segmentation have been proposed. In [12], a bayesian framework is used for dealing with both noise and blurry information. In [13], the Mumford and shah model is presented. The method consists of the minimization of a sum of criterions whose aim is to perform image restoration with homogeneous regions and thin boundaries.

Here, we propose a new regularization approach for MLEM deconvolution using FCM. The idea is to focus the intensity of voxels around cluster centroids during deconvolution process. Instead of using neighborhood information, regularization is performed according to a specified number of clusters that is given by the experimenter. The advantage is that small structures are preserved and sharp edges are retrieved. Moreover the image is segmented.

The paper is organized as follow. First, some background about deconvolution and FCM are given. It is followed by our proposed method which is then evaluated on simulated im-

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ages and on images acquired from fluorescence Diffuse Optical Tomography in vivo molecular imaging system.

2. BACKGROUND

2.1. Deconvolution

The general framework in deconvolution is based on the following model:

\[ i(x) = (o \otimes p)(x) + n(x), \quad (1) \]

where \( i \) denotes the recorded image, \( o \) denotes the real object, \( p \) is the Point Spread Function (PSF), \( n \) is an additive noise and \( \otimes \) is the convolution operator. MLEM deconvolution consists in reconstructing \( o \) by finding \( o = \arg \max_o \{ p(|i|) \} \). Because of the quantum nature of light, photon noise is Poisson distributed. Thus, \( o \) maximizes the likelihood function:

\[ p(|i|o) = \prod_x \left( \frac{(p \otimes o)(x)^{|i(x)|}}{|i(x)|} \right) \cdot \exp \left( -\frac{(p \otimes o)(x)}{|i(x)|} \right) \quad (2) \]

or minimizes the negative log-likelihood function given by:

\[ J_{ML} = \sum_x -i(x) \ln(p \otimes o)(x) + (p \otimes o)(x) + ln(i(x))! \quad (3) \]

Assuming that \( \sum_x p(x) = 1 \), finding the null derivative of (3) according to \( o(x) \) leads to the following updating:

\[ o^{t+1}(x) = o^t(x) \frac{i(x)}{(p \otimes o^t)(x)} \otimes p(-x) \quad (4) \]

where \( p(-x) \) corresponds to the mirrored PSF function. As mentioned in introduction, this update scheme has the drawback to amplify noise, that is why regularization is needed [1].

Regularization can be performed using L1 norm Total Variation (TV1) denoising approach [5]. The functional becomes:

\[ J_{MLTV1} = J_{ML} + \lambda_{TV1} \sum_x |\nabla o(x)| \quad (5) \]

where \( \nabla \) is the gradient operator, and \( \lambda_{TV1} \) is a parameter controlling the regularization term. It leads to the updating:

\[ o^{t+1}(x) = \frac{o^t(x) \frac{i(x)}{(p \otimes o^t)(x)} \otimes p(-x)}{1 - \lambda_{TV1} \text{div} \left( \frac{\nabla o(x)}{|\nabla o(x)|} \right)} \quad (6) \]

with the constraint \( \sum_j \mu_j = 1 \), where \( \mu_j(x) \) is the membership degree of \( i(x) \) according to cluster \( j \), and where \( ||i(x) - c_j|| \) is the norm expressing the similarity between \( i(x) \) and the cluster centroid \( c_j \).

2.2. Fuzzy C-Means (FCM)

FCM [8] is a clustering method allowing us to assign an object to two or more clusters with different membership degrees. Let \( j = \{1, \ldots, C\} \), where \( C \) is the number of cluster, FCM is based on the minimization of the objective function:

\[ J_{FCM} = \sum_x \sum_j \mu_j^m(x) ||i(x) - c_j||^2 \quad (7) \]

with the constraint \( \sum_j \mu_j = 1 \), where \( \mu_j(x) \) is the membership degree of \( i(x) \) according to cluster \( j \), and where \( ||i(x) - c_j|| \) is the norm expressing the similarity between \( i(x) \) and the cluster centroid \( c_j \). Because the intensities of voxels are brought close to the clusters, and the deconvolution with a regularization approach focusing the intensity of voxels around clusters.
and the signal vary slightly inside homogeneous regions. Using ML}_{TV1}, the contours are sharp and noise is not amplified. However the small region is not well retrieved and the pixel values between the two contaminated regions is higher than in simulated image (~0.25 instead of 0.2). Concerning ML}_{FCM2}, we observe that two classes of pixels (black and gray) have been regularized, whereas the contours of the third class (White pixels) are still blurry as using ML. This result is interesting because it shows that our method can be applied in the case of heterogeneous regions, affecting to the voxels different membership degrees according to the clusters. In conclusion, as long as the number of classes is known, the best deconvolution is obtained using our method. In biomedical cases, this number if often known by the experimenter thanks to its expertise in a pathology. Furthermore, the estimation of this number is still possible, using for example Bayesian Information Criterion as proposed in [11].

4.2. fluorescence Diffuse Optical Tomography (fDOT) images

In order to validate our method on biomedical images, we used images provided by fDOT in a mouse. It is a new imaging technique used to follow in 3-Dimensions (3D) a fluorescent probe in tissues [14]. Reconstructed images are extremely blurry, leading to imprecision that corresponds to a lack of knowledge [15]. It is the case at the contour of objects, and especially in the presence of small structures. In medical applications as oncoology, a precise segmentation is necessary in order to quantify the quantity of probes in tumors. Due to imprecision, fDOT image segmentation is difficult to achieve and measurements can not reflect the actual probe quantity in tissues.

The images are obtained as follow. First, a transparent capillary filled with 4 µL of fluorescent probes was inserted under the skin of a mouse (see Figure 2(a)). Then, a transillumination 685 nm-laser scan was performed at the region of interest (see Figure 2(a)), and 3D reconstruction was performed [14]. Figure 2(c) gives an example of reconstructed image. Voxel after reconstruction are $0.6 \times 0.6 \times 1$ mm$^3$. By changing the quantity of probes in the capillary, five quantities with the same volume were imaged: 2.6, 10.6, 21.2, 42.4 and 84.8 pMol. Assuming the autofluorescence of the mouse is null compared to the probes, the images give information about the total quantity of fluorescent signal in probes. Four segmentation methods are compared: a thresholding with a 0 threshold that allows us to measure the total signal quantity (Thresh), the FCM using 2 classes (FCM2), the MLTV1 deconvolution followed by FCM2 (ML$_{TV1}$) and our proposed method with two classes (ML$_{FCM2}$). $\lambda_{TV1}$ and $\Lambda_{FCM}$ was set to 0.1, allowing us to obtain sharp contours without noise amplification. Moreover, increasing these parameter values increases the size of the fluorescent region. Concerning ML$_{FCM2}$ the value was chosen in order to obtain fluorescent
Dedicated to blurry image segmentation, we propose to use FCM for regularization of MLEM deconvolution method. Regularization is achieved focusing the intensity of voxels close to the centroid of the cluster it belongs to. Furthermore, it allows us to deal with heterogeneity by affecting each voxel membership degrees according to the different clusters. Applied on simulated and fDOT images, the results show our method is well designed for segmenting extremely blurry images, and outperforms the TV1 regularization approach.

Our method removes blurry information corresponding to imprecision thanks to the knowledge about the number of clusters. It can be applied on blurry biomedical images. For dealing with both imprecision and uncertainty due to noise, our method could also integrate TV1 regularization.

In future works, the PSF of fDOT images will be estimated more accurately. The noise will also be estimated and the robustness to our method toward this noise will be evaluated. The automatic determination of the cluster number in each region to segment will also be studied.

5. CONCLUSION

6. REFERENCES


