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A Novel Region-Based Method For Intensity Inhomogeneities Image Segmentation And Denoising

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Abstract**——** Every image is implausibly vital for the medical field to grasp the facts of the user/patient. throughout this report we've got a bent to propose a general methodology (PURE-LET) to vogue and optimize a decent class of thresholding algorithms for denoising footage corrupted by mixed Poisson–Gaussian noise. to boot, this report jointly proposes a singular region-based technique for image segmentation, that's in degree extraordinarily position to vary intensity inhomogeneities inside the segmentation.

The methods related to the images with intensity inhomogeneities, we've got a bent to derive a district intensity agglomeration property of the image intensities, and description a district agglomeration criterion operate for the image intensities in associate passing neighborhood of each purpose. In the level set associate formulation, thes criterion defines associate energy in terms of the amount set method that represent a partition of the image domain and a bias field that accounts for the intensity irregularity of the image. For minimizing the energy, this technique is in degree extraordinarily position to at constant time section the image and estimate the bias field, and also the calculable bias field could even be used for intensity irregularity correction (or bias correction).

As associate application, our technique presents denoising results obtained on real footage of low-count analysis and has been used for segmentation and bias correction of resonance (MR) and CT footage with promising results.

I. Keywords— Mixed Poisson Gaussian-noise, intensity clustering, level set Formulation, PURE_LET.

I. INTRODUCTION

Image segmentation could be a basic drawback in image process and pc vision. in depth study has been created and plenty of techniques are projected , among that the active contour model [ACM] is one among the foremost strategies. The fundamental plan of active contour model is to evolve a curve below some constraints to extract the required object. per the character of constraints, the present active contour models will be classified into 2 types: edge-based models and region-based models. Image segmentation plays a very important role within the field of image analysis and pattern identification. The goal of the segmentation method is to partition a picture into regions that are uniform (uniform) with reference to one or a lot of self characteristics and options. Active contour strategies are applied in a very wide selection of issues together with visual pursuit and image segmentation. the fundamental plan is to permit a contour to deform therefore on minimize a given energy purposeful so as to supply the required segmentation. 2 main classes presented in active contours: edge-based and region-based. In edge-based active contour models utilize image gradients so as to spot object boundaries. Region-based active contour models [ACM] have several benefits over edge-based ones.

In this paper, we tend to propose a completely unique region-based methodology for image segmentation. From a usually accepted model of pictures with intensity inhomogeneities, we tend to derive an area intensity cluster property, and so outline an area cluster criterion operate for the intensities in a very neighborhood of every purpose. This native cluster criterion is integrated over the neighborhood center to outline associate degree energy purposeful, that is regenerate to level set formulation. step-down of this energy is achieved by associate degree interleaved method of level set evolution and estimation of the bias field. As a very important application, our methodology will be used for segmentation and bias correction of resonance (MR) pictures.

In this paper in Section IV PURE_LET formula is employed to denoise the image, and apply the cluster formula. In section V, level segmentation method has been represented. In section VI, the energy formulation method is completed for bias field detection. In section VIII, minimizing the energy set victimisation DRLSE(distance regularize level set evaluation).

II. RELATED WORKS

Intensity inhomogeneity often occurs in medical fields, which presents a challenges in image segmentation. The often used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, that is mostly fail to provide accurate segmentation results due to the intensity inhomogeneity.

In the level set method, contours or surfaces are represented as the zero level set of a higher dimensional function is also been said as *level set function*. Along with the level set function, the image segmentation problem can be considerable and solved in a principled way based on the established mathematical theories and partial differential equations (PDE). The merits of the level set method is curves and surfaces that can be processed by a Cartesian grid without having to parameterize of the objects.

Categorized into two major classes: *region-based models* and *edge-based models*. Region-based models is mainly used to identify each region of interest by using a region descriptor to guide the motion of the active contour. It is very difficult to define a region descriptor for images with intensity inhomogeneities.

Commonly the region-based models are based on the assumption of intensity homogeneity. A sample example is *piecewise constant (PC) models* proposed in. mostly the level set methods are based on a general *piecewise smooth (PS)* formulation originally proposed by Mumford and Shah. The piecewise smooth method has been used in the region based model and in the piecewise constant model has been used in the edge based models.

This model is used for validation by using the synthetic images and real images of different modalities, with appropriate performance in the presence of intensity inhomogeneities. Experiments show that the edge based image segmentation method is more robust to initialization, and more faster and more perfect than the well-known piecewise smooth model. As an application, the piecewise constant method is implmented by segmentation and bias correction of magnetic resonance (MR) images with accurate results.

The denoising process is also express as a linear expansion of thresholds (LET) that to optimize by relying on a truly data adaptive unbiased estimate of the mean-squared error (MSE). The PURE LET algorithm also present denoising results obtained on input images of less count fluorescence microscopy.

Multi-phase level set segmentation for image segmentation using the Mumford and Shah model, for both, the piecewise constant and piecewise smooth optimal approximations. To obtain an active contour model for object detection, the basic idea was to look for a particular partition of a given image into two regions,

a. One representing the objects to be detected.
b. The second one representing the background.

The proposed method is also a active contour model but without the edges based segmentation.

The Piecewise-Constant Case

The main goal of this paper is to look for a new multiphase level set model with which it can represent more than two segments or phases, triple junctions and other complex topologies, in an efficient way.

Level set functions has to represent *n* different phases or segments with complex topologies.

The Piecewise-Smooth Case

In this propose a multi-phase level set formulation and algorithm for the general problem of Mumford and Shah (1989) in image processing, to compute piecewise smooth optimal approximations of a given image.

We consider the cases:

1. In one dimension:
   For signal segmentation and denoising, it show that, using only one level set function, it can represent any signal with any number of segments in the partition.
2. In two dimensions:
   It generalize the 2-phase piecewise-constant model using only one level set function, that is different regions of distinct intensities can be represented and detected with the correct intensities.

Following the idea of the multi-phase level set partition from the previous section, they shows that, in the piecewise-smooth case it uses only two level set functions, producing up to four phases. Here they have explained that the piecewise smooth case is low cost then the piecewise constant case.

III. IMPLEMENTATION PROPOSAL

Every image is very important for the medical field to realize the facts of the user/patient. A general methodology (PURE-LET) to design for denoising images corrupted by mixed Poisson–Gaussian noise. In addition, this report also proposes a novel region-based method for image segmentation, which is used to processed with intensity inhomogeneities in the segmentation. Based on the model of images with intensity inhomogeneities, to derive a local intensity clustering property, they cluster for the image intensities in a neighborhood of each point. In a level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image. Therefore, by minimizing the energy level, this method is capable to segment the image and find the bias field, and the detected bias field can be used for intensity inhomogeneity correction (or bias correction).

IV. PURE-LET

The PURE-LET(Poisson-Gaussian Unbiased Risk Estimate Linear Expansion of Thresholds) algorithm is the best algorithm for image denoising in intensity inhomogeneities images, then the SURE-LET algorithm. The PURE-LET approach in three main directions.

1. Lift the restricted use of the unnormalized Haar wavelet transform has been generalizing to arbitrary (redundant) transform-domain (nonlinear) processing.
2. Consider a more realistic noise model: a Poisson random vector degraded by AWGN(additive-white-Gaussian-noise), for which we derive a current unbiased MSE estimate; this new estimate, for which we keep the name PURE.
3. Show that PURE can be used to globally optimize a LET spanning several (redundant) bases.

A generic PURE-LET framework for designing and jointly optimizing a broad class of (redundant) transform-domain nonlinear processing. To obtain a computationally fast and efficient algorithm for image denoising can be obtained by implementation of PURE concept. For each nonlinearly processed sub band, the reliability of this approximation can be controlled, ensuring near optimal MSE performances for the considered class of algorithms.

4.1 Choice of $\bar{\mathbf{D}}$—Group-Delay Compensation (GDC)

In an undecimated wavelet transform (UWT), the measuring of coefficients of the low-pass residual at a given scale j could be used as a reliable estimation of the signal-dependent noise variance for each band-pass sub-band from the same scale , up to the scale-dependent factor $\beta_j = 2^{-j/2}$.

$$H(z^{-1})Q(z^{-1}) = G(z^{-1})R_1(z)$$

$$\begin{cases} \bar{H}_j(z) = 2^j Q(z^{2^{j-1}})H_j(z) \\ \qquad = Q(z^{2^{j-1}})H(z)H(z^2)\cdots H(z^{2^{j-1}}), \\ \qquad\qquad \text{for } j = 1\ldots J \\ \bar{H}_{J+1}(z) = 2^J H_J(z) \\ \qquad = H(z)H(z^2)\ldots H(z^{2^{J-1}}). \end{cases}$$

In this completed M-block discrete cosine transform(BDCT) representation, the low-pass residual band will immediately serve as a coarse estimate of the noise variance for each bandpass subband, since the filters of the BDCT all have the same group delay.

4.2 Computation of Transform-Dependent Terms

To compute the MSE estimate, we need to formulate various terms that depends only on the choice of transformation.

1) Computation of a :
In the case of periodic conditions, we have that

$$\operatorname{diag}\{\mathbf{D}_j\mathbf{R}_j\} = \begin{cases} \frac{1}{M_j}[\underbrace{1\,1\ldots1}_{N \text{ times}}]^{\mathrm{T}}, & \text{for } j = 1\ldots J \\ \frac{1}{M_J}[\underbrace{1\,1\ldots1}_{N \text{ times}}]^{\mathrm{T}}, & \text{for } j = J+1 \end{cases}$$

where, for multiscale filterbanks, $M_j = 2^j$ is the downsampling factor. For an overcomplete BDCT, $M_j = M$, where, M will be considered as the size of the blocks.

2) Computation of $\operatorname{diag}\{\bar{\mathbf{D}}\mathbf{R}\}$, $\operatorname{diag}\{(\mathbf{D}\bullet\mathbf{D})\mathbf{R}\}$, $\operatorname{diag}\{(\bar{\mathbf{D}}\bullet\bar{\mathbf{D}})\mathbf{R}\}$, and $\operatorname{diag}\{(\mathbf{D}\bullet\bar{\mathbf{D}})\mathbf{R}\}$.

4.3 Thresholding Function

Now we have to use a subband-dependent pointwise thresholding function defined for

$$\Theta(\mathrm{w}, \bar{\mathrm{w}}) = [\theta_j(w_{j,n}, \bar{w}_{j,n})]_{(j-1)N+n}.$$

In the case of Poisson data, we need a signal-dependent transform-domain threshold to take into account the non stationary of the noise. Consider the unit-norm filters, the variance σ^2 of the AWGN is preserved in the transformed domain. In the estimation of the variance of the Poisson-noise component is given by the magnitude $|\bar{w}|$ of, up to the scale-dependent factors $\beta_j = 2^{-j/2}$ and $\beta_j = M^{-1/2}$ for a multiscale transform and for an overcomplete BDCT, respectively. Therefore, we propose the signal-dependent threshold

$$t_j(\bar{w}) = \sqrt{\beta_j|\bar{w}| + \sigma^2}$$

which is then embedded in a subband-dependent thresholding function, similar to the one proposed for AWGN reduction in redundant representations

$$\theta_j(w,\bar{w}) = a_{j,1}\cdot \underbrace{w}_{\theta_{j,1}(w,\bar{w})} + a_{j,2}\cdot \underbrace{w\exp\left(-\left(\frac{w}{3t_j(\bar{w})}\right)^8\right)}_{\theta_{j,2}(w,\bar{w})}.$$

To compute the MSE estimate given , a differentiable (at least up to the second order) approximation of the absolute-value function is required.

$$\hat{\epsilon} = \frac{1}{N}\|f(y)-y\|^2 - \frac{1}{N}1^T y - \sigma^2 + \frac{2}{N}\left(\Theta_1(w,\bar{w})^T(D\bullet R^T)y + \Theta_2(w,\bar{w})^T(\bar{D}\bullet R^T)y\right)$$
$$+\frac{2\sigma^2}{N}\left(\mathrm{diag}\{DR\}^T\Theta_1(w,\bar{w}) + \mathrm{diag}\{\bar{D}R\}^T\Theta_2(w,\bar{w})\right)$$
$$-\frac{2\sigma^2}{N}\left(\mathrm{diag}\{(D\bullet D)R\}^T\Theta_{11}(w,\bar{w}) + \mathrm{diag}\{(\bar{D}\bullet\bar{D})R\}^T\Theta_{22}(w,\bar{w}) + 2\,\mathrm{diag}\{(D\bullet\bar{D})R\}^T\Theta_{12}(w,\bar{w})\right)$$

4.4 Denoising in Mixed Bases

In the generalized PURE-LET framework for -band undecimated filterbank, the whole transform-domain thresholding is rewritten as

$$f(y) = \sum_{j=1}^{J}\sum_{k=1}^{2} a_{j,k}\underbrace{R_j\Theta_{j,k}(D_j y, \bar{D}_j y)}_{f_{j,k}(y)} + \underbrace{R_{J+1}D_{J+1}y}_{\text{lowpass}}.$$

In order to get the best out of several transforms, therefore we decided to make the LET span several transformed domains with complementary properties (e.g., UWT and overcomplete BDCT)

$$f(y) = \sum_{k=1}^{K_1} a_k f_k^{\mathrm{UWT}}(y) + \sum_{k=1}^{K_2} b_k f_k^{\mathrm{BDCT}}(y) + \cdots$$

In this case, the union of several transforms can be interpreted as an overcomplete dictionary of bases which sparsely represents a wide class of natural images.

4.5 PSNR

The PSNR is the error detecting ratio has been calculated between the maximum power of a signal and the power of corrupting noise that affects the fidelity of its representation. More number of signals will have a large and wide dynamic range.

The signal in this case is the original data, and the noise which is presented in the image the error introduced by compression. By comparing the compression it is used as an approximation for the human perception of reconstruction measurement, In some cases one reconstruction may appear to be closer to the original image, not an another image, even though if it has the minimum of the PSNR value, that would normally indicate, that the newer construction of increased quality

It can be easily defined by using the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The PSNR is defined as:

$$PSNR = 10\cdot\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\cdot\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

Here, MAX_I is the maximum possible pixel value of the image. The pixels in the imgas are represented using 8 bits per image,that is 255.

V. LEVEL SET SEGMENTATION

The physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image can be modeled as I=bJ+n Where J is the input image, b is the element that is consider for the intensity inhomogeneity, and n is additive noise. The component J is referred to as a bias field (or shading image). The true image measures an intrinsic physical property of imaged, that has been taken as an piecewise (approximately) constant. The bias field has been assumed to be varying slowly and the additive noise n has been taken as a zero-mean Gaussian noise.

The image as a function I:Ω->Ř defined on a continuous domain Ω. The assumptions about the true image J and the bias field b can be stated more specifically as follows: A1=The bias field b slowly varying, which implies b≍ constant in a neighborhood of each point.A2=True image J approx take N dist constant values c1,c2,..cn in disjoint region Ω1,Ω2,..Ωn i.e {Ωi}N ^ i=1 forms a partition of the domain image.

5.1 LOCAL INTENSITY CLUSTERING PROPERTY

Intensity inhomogeneities often lead to overlap between the distributions of the intensities in the regions Ω1, Ω2…. ΩN. Based on the image model in and the assumptions A1 and A2, we are able to derive a useful property of local intensities that has been referred to a local intensity clustering property. Actually specifies that to be consider a circular neighborhood with a radius centered at each point y Є Ω.,

$$b(\mathbf{x}) \approx b(\mathbf{y}) \quad \text{for} \quad \mathbf{x} \in \mathcal{O}_{\mathbf{y}}.$$

Thus, the intensities b(x)J(y), in each subregion O_Y ∩ Ωi are close to the constant b(y)c, i.e.
where n(x) is additive zero-mean function for mixed noise. The intensities has been set as follows

$$\mathbf{I}_{\mathbf{y}}^{i} = \{I(\mathbf{x}) : \mathbf{x} \in \mathcal{O}_{\mathbf{y}} \cap \Omega_i\}$$

And the same local intensity clustering property is used to calculate the next newer method for image segmentation and bias field estimation.

VI. ENERGY FORMULATION

The K-means clustering is an algorithm which is an set of process to minimize the clustering criterion, That has been written in a sequences form as follows:

$$F_{\mathbf{y}} = \sum_{i=1}^{N} \int_{\mathcal{O}_{\mathbf{y}}} I(\mathbf{x}) - m_i|^2 u_i(\mathbf{x}) d\mathbf{x}$$

where k(y-x) is described as a nonnegative window function, said to be kernel function. where k(y-x) is introduced as a nonnegative window function, called kernel process. The local clustering criterion function Єy evaluates the classification of the intensities in the neighborhood O_Y given by the partition { O_Y ∩ Ωi} of O_Y .The smaller the value of Єy , the better the classification. Therefore, we need to jointly minimize Єy for all in Ω . This can be achieved by minimizing the integral of Єy with respect to y over the image domain Ω. Therefore, we define an energy Є_Δ ∫Єy dy i.e..

$$\mathcal{E} \triangleq \int \left(\sum_{i=1}^{N} \int_{\Omega_i} K(\mathbf{y}-\mathbf{x}) \; I(\mathbf{x}) - b(\mathbf{y}) c_i \;^2 d\mathbf{x} \right) d\mathbf{y}.$$

VII. LEVEL-SET SEGMENTATION STEPS

Step 1): we consider the image I as a function I:Ω->Ř defined on a continuous domain Ω.
Step 2): Then assume about the true image J and the bias field b can be stated as follows:A1=The bias field b slowly varying, which implies b≃ constant in a neighborhood of each point.A2=True image J approx take N dist constant values c1,c2,..cn in disjoint region Ω1,Ω2,..Ωn i.e {Ωi}N^i=1 forms a partition of the domain image.
Step 3): Based on the image model and the assumptions A1 and A2, we derive a local intensity clustering property which considers a circular neighborhood with a radius centered at each point y Є Ω. b (x) ≈b (y) for x .
Step 4): Then K-means algorithm is used as an iterative process to minimize the clustering criterion.
Step 5): Then the level set formulation is done by minimization of energy. The level set formulation of the energy Є for the cases of N=2 and N>2 , called two-phase or Distance Regularized Level Set Evolution (DRLSE) formulation.
Step 6): By minimizing the energy, we obtain the result of image segmentation given by the level set function ø and the estimation of the bias field .

VIII. ENERGY MINIMIZATION

By minimizing the energy, we obtain the result of image segmentation given by the level set function ø and the estimation of the bias field b. The energy minimization is achieved by an iterative process: in each iteration, we minimize the energy With respect to each of its variables.

1) Energy Minimization With Respect to ø: For fixed and ,the minimization of $\mathcal{F}(\phi, \mathbf{c}, b)$ with respect to can be achieved by using standard gradient descent method, used for solving the gradient flow equation

$$\frac{\partial \phi}{\partial t} = -\frac{\partial \mathcal{F}}{\partial \phi}$$

where $\partial \mathcal{F}/\partial \phi$ is the Gâteaux derivative of the energy $\mathcal{F}$.

2) Energy Minimization With Respect to c: For fixed ϕ and b, the optimal c, that minimizes the energy $\mathcal{E}(\phi, \mathbf{c}, b)$, denoted by , is $\hat{\mathbf{c}} = (\hat{c}_1, \cdots, \hat{c}_N)$ given by

$$\hat{c}_i = \frac{\int (b * K) I u_i dy}{\int (b^2 * K) u_i dy}, \quad i = 1, \cdots, N$$

with $u_i(\mathbf{y}) = M_i(\phi(\mathbf{y}))$.

3) Energy Minimization With Respect to b: For fixed ϕ and b, the optimal c, that minimizes the energy $\mathcal{E}(\phi, \mathbf{c}, b)$, denoted by $\hat{b}$, is given by

$$\hat{b} = \frac{\left(IJ^{(1)}\right) * K}{J^{(2)} * K}$$

IX. CONCLUSION

In this report, we have provided an unbiased estimate of the MSE for the estimation of Poisson intensities degraded by AWGN, a practical measure of quality that we called PURE. We have then defined a generic PURE-LET framework for designing and jointly optimizing a broad class of (redundant) transform-domain nonlinear processing.

To obtain a computationally fast and efficient algorithm for undecimated filterbank transforms, we have proposed a first-order Taylor-series approximation of PURE. For each nonlinearly processed subband, the reliability of this approximation can be controlled, ensuring near optimal MSE performances for the considered class of pseudo-code.

The proposed solution also favorably compares with some of the most recent multiscale methods specifically devised for Poisson data. We have shown that our PURE-LET strategy constitutes a competitive solution for fast and high-quality Denoising of real fluorescence microscopy data.

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