Image Restoration of Medical Images using Patch Based Sparse Representation with Non-Convex Hybrid Total Variation

Aswathi V M
PG Scholar,Dept.of CSE
Vimal Jyothi Eng.College
Chemperi, Kannur

James Mathew
Assist.Profesor
Vimal Jyothi Eng.College
Chemperi, Kannur

Abstract:- **The restoration of images corrupted by blur and noise is a key issue in medical and biological image processing. In this paper we consider restoration of medical images with poisson noise and blur. Sparse representations of images provide better results for image recovery. In this paper we propose a model containing three terms: a patch-based sparse representation prior over a learned dictionary, non convex hybrid total variation method that helps to reduce staircase artifacts in restored smoothened regions while preserving valuable edge information in the images and a data-fidelity term capturing the statistics of Poisson noise. An alternating minimization technique combined with variable splitting is used for solving resulting optimization problem. The proposed method provides better results in terms of peak signal to noise ratio and visual quality.**

1. INTRODUCTION

Image denoising remove the noise in the image without sacrificing importantant structures such as edges. It is unavoidable in real applications such as in biomedical imaging, microscopy, astronomical imaging where low intensity signals are frequently encountered. The most important degradation in this area is poisson noise due to quantum nature of light. In this paper we addresses image denosing problem with an image x is measured in presence of noise n with standard deviation σ. Then the measured image y is represented as

$$y=x + n$$

The main desire is to find out an algorithm that remove noise and recover the image that is as close as possible to original image x.

A widely-used regularization criterion in image processing is total variation (TV) [1], which is known to well preserve edges in images. However, TV regularization is also known to oversmooth textured regions, which may cause the loss of important details. Many patch-based sparse priors have been studied for image restoration. One approach exploits a heavy-tailed gradient distribution of natural images [4]. Elad and Aharon [5] proposed an effective denoising method (called K-SVD) based on a sparse and redundant representation: their algorithm first learns an optimal over-complete dictionary from the observed noisy image patches, and then recovers each image patch via a linear combination of only a few atoms in the learned dictionary. Another remarkable denoising method relying on a sparse representation is the BM3D algorithm proposed by Dabov et al. [6]. Similar patches are first stacked into 3D arrays, and then jointly denoised using collaborative filtering in the 3D transformed domain. The BM3D method is very efficient, and does not need to find an explicit dictionary.

Recently sparse approximation of images has shown to be efficient approaches for image recovery. In proposed model it containing three terms: a patch-based sparse representation prior over a learned dictionary, non convex hybrid total variation method that helps to reduce staircase artifacts in restored smoothened regions while preserving valuable edge information in the images and a data-fidelity term capturing the statistics of Poisson noise. Mathematically a degraded observed image f is represented as,

$$F=P\ (Hu)$$

Where u is the unknown real image, H is stands for blur and P denotes the effect of noise.

In proposed model use KSVD (K means singular value decomposition) for sparse and redundant representations. KSVD algorithm first learns an optimal overcomplete dictionary from the observed noisy image patches, and then recover image patch via linear combination of only a few atoms in the dictionary.

Most previous noise removal methods are designed to work with Gaussian noise. Unfortunately, Gaussian distributions provide only a limited approximation in most real applications. Lots of methods are proposed for Poisson noise removal: 1)Simply recover the image using a method recovered for Gaussian noise removal; 2)transform Poisson noise into near Gaussian noise by applying appropriate transform to the noisy image; 3)remove Poisson noise directly via data fidelity term derived from Poisson noise statistics. In this paper we consider the third category.

It is important to choose a regularizer in the variational framework and a suitable prior in the statistical framework. In [1] Rudin–Osher–Fatemi (ROF) proposed a total variational(TV) model for image denoising. TV can remove noises and simultaneously preserve edges and meaningful features. However, in the presence of noises, it may cause staircase artifacts. i.e., smooth transition regions in the intensity tend to be oversegmented to form constant stairs. To introduce higher-order derivative information into the energy is another approach to overcome staircase artifacts.

To introduce higher-order derivative information into the energy is another approach to overcome staircase artifacts. Originally, Lysaker et al. [3] proposed the following Lysaker–Lundervold–Tai (LLT) model:

$$\min \int_{\Omega} |\nabla^2 u| + \frac{\mu}{2}\int_{\Omega}(u-f)^2$$

Where $\nabla^2 u = \nabla(\nabla u)$

Where $\int_{\Omega} |\nabla^2 u|$ is the higher order derivative of u. The advantage of this model is its ability to process signals with smooth changes in the intensity. The close approximation of smooth transition regions by higher-order derivatives can remove staircase artifacts to a remarkable degree. However, the numerical computation of the LLT model is difficult owing to its
non-linearity and non-differentiability, which are also problems of the ROF model.

A major challenge that a model using only higher-order derivatives faces is to maintain edges in its reconstructions. Hybrid models that use both lower- and higher-order derivatives have been proposed to on the one hand, preserve the discontinuities along edges, and on the other, recover smooth regions.

2. PROPOSED SYSTEM

2.1 Image denoising using patch based sparse representation prior

In patch based sparse representation we have to model M for a signal x having N*1.We have to develop a dictionary of size N*K. Where N is the dimension of the signal and K is the size of the dictionary. The dictionary has K columns and each column is called an atom. If K>n, then dictionary is called over complete dictionary. If K=N then it is called complete dictionary. If K<N then it is called under complete dictionary. There is a matrix α having dimension K*1, it is a sparse and random vector. Then multiplying D*α gives the signal X, that we are trying to model. Non zero entries of α are very small. There is supposing L nonzero entries of α. That is,
||α||0 ≤L
Then our signal model is,
X= D*α where ||α||0 ≤L
We have to find out α using the optimal matching pursuit (OMP) algorithm

$$\hat{\alpha} = \arg\min_{\alpha \in R^k} \| \alpha \|_{0,} \; s.t. \| D\alpha - x \|_2 \le \varepsilon$$

Algorithm for solving the above problem:

Step 1: Set L=1

Step 2: Find an atom in D that best matches the signal

Step 3: Solve the least square problem such that

$$\min_{\alpha} \| D\alpha - x \|_2 \le \varepsilon$$

Step 4: If LS error is less than the error ε then done. Otherwise set L=L+1 and find next atom that best fit the residual

Following sparse representation assumption using KSVD proposed to achieve Guassian noise removal with the variation model.

$$\min_{\{\alpha_{i,j}\},u,D} \sum_{(i,j)\in A_s} \mu_{ij} \| \alpha_{ij} \|_0 + \sum_{(i,j)\in A_s} \| D\alpha_{ij} - R_{ij}u \|_2^2 + \lambda \| u - g \|_2^2$$

Where binary matrix Rij corresponds to extraction of $\sqrt{N} * \sqrt{N}$ block from image at location (i,j).Hidden parameter µij >0 depends on optimization procedure. The first two terms corresponds to sparsity assumption while last terms controls data fidelity, weighted by positive fidelity λ.

Image encounterd in real applications are structured data that presents a lot of repeated patterns,in particular edges,smooth regions, and textures. This is probably why methods incorporating sparse and adaptive priors have exhibited very good performances. In the proposed model we use the sparse representation prior as regularization term, and the data fidelity term to model blur and poisson noise. To overcome the artifacts sometimes caused by patch-based priors in deblurring tasks , we add a non-convex hybrid TV regularization

2.2 Non-convex hybrid total variation

Consider a model that substitutes $\| \nabla u \|_2^{\alpha}$ for a regularizer [1] in the ROF total variational model. This model minimizes the support of image gradient and yields a piecewise constant solution, as is done by the ROF model. This model works effectively for an image containing mainly piecewise constant regions and sharp edges. However it can lead to staircase effects when applied to a wide range of images that include smooth transition regions instead of being dominated by piecewise constant regions.

In [12] HOTV is more suitable for a relatively wide range of image types to produce piecewise linear solutions the term $\int_{\Omega} |\nabla^2 u|$ was justified as an appropriate higher-order extension of TV, which proved that it can result in relatively good image restoration with smooth intensity changes, such as for biomedical images, as well as inherit the attractive properties of TV such as convexity and rotation invariance. This research led us to choose $\| \nabla^2 u \|_2^{\alpha}$ as the higher-order extension of TV among several available choices. Inspired by the above observations, we attempt to introduce the non-convexity of HOTV instead of TV.

We replace the HOTV regularizer of the LLT model with $\| \nabla^2 u \|_2^{\alpha}$ to minimize the support of HOTV.

$$\min_u \| \nabla^2 u \|_2^{\alpha} + \frac{\mu}{2} \| u - f \|_2^2 \quad \text{where } \alpha<1.$$

We call the modified model the non-convex HOTV model. Even though non-convexity increases the difficulty in analyzing and numerically solving the model, it yields better results than thoseobtained by convex models such as the ROF and LLT models. However, the drawback of the non-convex HOTV is that it can blur edges.

In order to overcome this drawback we introduce, the hybrid model. The combinations of TV and HOTV for a regularizer could balance the preservation of edges and smoothness within homogeneous regions in an image. We propose only the non-convex hybrid TV model for the image denoising problem. To maximize the benefits of non-convex TV and HOTV regularizers and to overcome their weakness, we consider a suitable combination of the two regularizers as for the convex case. We call the resulting model a non-convex hybrid TV model. The combination of the non-convex TV and the non-convex HOTV reduces the staircase artifacts in smooth transition intervals and simultaneously preserves edges.

Figure a

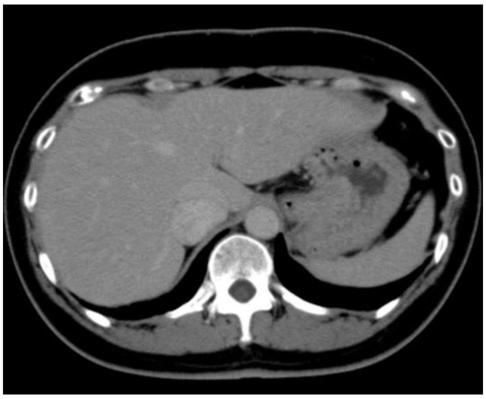

Figure c

3. EXPERIMENTAL RESULTS

Table below shows the peak signal to noise ratio and mean squre error of different images.

Table 1. Peak signal to noise ratio with different peak pixel value and mean squre error of images

Image	PSNR	MSE
Figure a	36.86	0.185
Figure b	37.92	0.144
Figure c	38.94	0.066
Figure d	36.74	0.213

Figure b

Figure d

5. CONCLUSION

In this paper we proposed an image denoising method that recover images from poisson noise and blur. The model contains two priors: a patch-based sparse representation prior over a learned dictionary, non convex hybrid total variation method that helps to reduce staircase artifacts in restored smoothened regions while preserving valuable edge information in the images. The proposed method provide better performance with higher PSNR and minimum mean square error values and improves quality of recovered image.

.

REFERENCES

[1] Leonid I. Rudin, Stanley Osher, and Emad Fatemi, "Nonlinear total variation based noise removal algorithms", Phys. D, Vol. 60, pp. 259–268, November 1992.

[2] David S. C. Biggs and Mark Andrews, "Acceleration of Iterative Image Restoration Algorithms", APPLIED OPTICS, Vol. 36, No. 8, pp. 1766-1775, 10 March 1997.

[3] M. Lysaker, A. Lundervold, X.-C. Tai, Noise removal using fourth-order partial differential equation with application to medical magnetic resonance images in space and time, IEEE Trans. Image Process. 12 (12) (2003) 1579–1590.

[4] T. Cho, N. Joshi, C. Zitnick, S. Kang, R. Szeliski, and W. Freeman, "A content-aware image prior," in Proc. IEEE Comput. Vis. Pattern Recognit., San Francisco, CA, 2010, pp. 169–176.

[5] Michael Elad and Michal Aharon, "Image denoising via sparse and redundant representations over learned dictionaries", IEEE Trans. Image Process., Vol. 15, No. 12, pp. 3736–3745, Dec. 2006.

[6] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian, "Image denoising by sparse 3-d transform-domain collaborative filtering", IEEE Trans. Image Process., Vol. 16, No. 8, pp.2080–2095, Aug. 2007.

[7] Reginald L. Lagendijk and Jan Biemond, "Basic Methods for Image Restoration and Identification", In: A. C. Bovik, the Essential Guide to Image Processing, Academic Press, United States of America, pp. 326 – 330, 2009.

[8] Priyam Chatterjee and Peyman Milanfar, "Clustering-based denoising with locally learned dictionaries", IEEE Trans.Image Processing, Vol. 18, No. 7, pp. 1438–1451, July 2009.

[9] Y. Tai, P. Tan, and M. S. Brown, "Richardson-Lucy deblurring forscenes under projective motion path," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 8, pp. 1603–1618, Aug. 2011.

[10] Liyan Ma, Lionel Moisan, Jian Yu, and Tieyong Zeng "A Dictionary Learning Approach for Poisson Image Deblurring" IEEE Transactions on medical imaging, vol. 32, no. 7, July 2013

[11] Dejee Singh, Mr R. K. Sahu "A Survey on Various Image Deblurring Techniques" International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 12, December 2013

[12] Seungmi Oh, Hyenkyun Woo, Sangwoon Yun and Myungjoo Kang," Non-convex hybrid total variation for image denoising"elsevier J. Vis. Commun. Image R. 24 (2013) 332–344

[13] Dr. S. Sakthivel, M. Parameswari " A Survey on Sparse Representation based Image Restoration" International Journal of Computer Science and Business Informatics Vol. 12, No. 1. APRIL 2014