ISSN:0975-9646

Garima Goyal / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (4) , 2014, 5120-5124

Impact & Analysis of DVROFT Filter on TEM Image

Garima Goyal
Assistant Professor, Jyothy Institute of Technology
Bangalore, India

Abstract-TEM images are rapidly gaining prominence in various sectors like life sciences, pathology, medical science, semiconductors, forensics, etc. Hence, there is a critical need to know the effect of existing image restoration and enhancement techniques available for TEM images. This paper primarily focuses on DVROFT filter. After simulation it is observed that the SNR and PSNR ratios obtained for TEM image is much higher than those obtained for normal image. DVROFT give better performance than the others in case of both greyscale TEM and colored TEM images.

Index Terms: TEM, Filter, SNR, PSNR

I. INTRODUCTION

A lot of work has been undertaken in the restoration and enhancement of ultrasound, MRI and other TEM images of different formats but the same efforts are yet to be made extensively for the transmission electron microscope (TEM) images. TEM images are rapidly gaining prominence in various sectors like life sciences, pathology, medical science, semiconductors, forensics, etc. Hence, there is a critical need to know the effect of existing image restoration and enhancement techniques on TEM images. There are multiple available techniques for improving the image quality.

II. LITERATURE SURVEY

The total variation has been introduced in Computer Vision first by Rudin, Osher and Fatemi [1], as a regularizing criterion for solving inverse problems. It has proved to be quite efficient for regularizing images without smoothing the boundaries of the objects. Antontonin proposed a relaxation method , an alternative method that was able to handle the minimization of the minimum of several convex functionals [2]. In 1995, an improvement to the choice of the regularization parameter involved in a deconvolution procedure was proposed. It was based on a statistical model allowing a good estimation of the spectral signal-to-noise ratio [3].Based on the CGM model, Chambolle (C) in [4] developed an efficient dual approach to minimize the scalar ROF model. C's algorithm is faster than CGM even if the convergence of C's scheme is linear and the CGM's scheme is quadratic. C's algorithm is faster because the cost per iteration to use CGM is higher (CGM needs to solve a linear system at each iteration).

In 1999, a modified version of classical regularization techniques. Instead of using regularization in order to reduce the measurement noise effect of cancelling the inverse filter singularities, and to restore the original signal, a prefiltering was performed before the regularization. This prefiltering was obtained by using a Wiener filter based on a particular modelization of the signal to be restored [5].

A recent fast minimization algorithm for the scalar ROF model was proposed by Darbon and Sigelle (DS) in [6] based on graph cuts. Although C's algorithm is not as fast as the model of DS to solve the variational scalar ROF model, it is still fast and presents some advantages compared with CGM and DS. First, C's model use the exact scalar TV norm whereas CGM model regularizes it to minimize it. Then, the numerical scheme of [4] is straightforward to implement unlike the CGM and DS algorithms. Besides, the TV norm of DS is anisotropic whereas the TV norm of C is isotropic. Finally, we will see that the C's model extends nicely to color/vector images whereas the question of extension is open for the CGM model and the generalization of DS model to color images is not as efficient as in the scalar case [7]. X. Bresson extended the Chambolle's model [4] to multidimensional/vectorial images. Unlike the proposed vectorial scheme does not regularize the VTV to minimize it. Finally, the numerical solution converges to the continuous minimizing solution in the vectorial BV space. This VTV minimization scheme to several standard applications such as deblurring, inpainting, decomposition, denoising on manifolds [8].

Paul proposed a simple but flexible method for solving the generalized vector-valued TV (VTV) functional with a non negativity constraint. One of the main features of this recursive algorithm is that it is based on multiplicative updates only and can be used to solve the denoising and deconvolution problems for vector-valued (color) images [9]. In 2009, for image restoration, edge-preserving regularization method was used to solve an optimization problem whose objective function has a data fidelity term and a regularization term, the two terms are balanced by a parameter λ. In some aspect, the value of λ determines the quality of images. A new model to estimate the parameter and propose an algorithm to solve the problem was established. The quality of images was improved by dividing it into some blocks [10].

For the first time TV Regularization method was applied to fMRI data, and show that TV regularization is well suited to the purpose of brain mapping while being a powerful tool for brain decoding. Moreover, this article presents the first use of TV regularization for classification [11]. In the particular techniques, the SR problem is formulated by means of two terms, the data-fidelity term and the regularization term. The experimentation is carried out with the widely employed L2, L1, Huber and Lorentzian estimators for the data-fidelity term. The Tikhonov and Bilateral (B) Total Variation (TV) techniques are employed for the regularization term. The extracted conclusion is that in case the potential methods present common data-fidelity or regularization term, and frames are noiseless, the method which employs the most robust regularization or data-fidelity term should be used [12].

III. DUAL VECTORIAL ROF FILTER

Regularity is of central importance in computer vision. Many problems, like denoising, deblurring, superresolution and inpainting, are ill-posed, and require the choice of a good prior in order to arrive at sensible solutions. This prior often takes the form of a regularization term for an energy functional which is to be minimized. For optimization purposes, it is important that the regularizer is convex, since only then one can hope to always find a global optimum of the energy within reasonable time. Furthermore, images in the real-world can be observed to generally be piecewise smooth. For these reasons, the total variation (TV) of a function has emerged as a very successful regularizer for a wide range of applications. It is convex, but still discontinuity-preserving, as it assigns the same cost to sharp and smooth transitions. While most existing work focuses on scalar valued functions, the generalization to vector valued (color or multichannel) images remains an important challenge.

For a greyscale image modeled as a differentiable function function $u: \Omega \rightarrow \mathbb{R}$ on a domain $\Omega \subset \mathbb{R}^m$ the scalar total variation TV(u) is defined as the integral over the Euclidean norm $|.|_2$ of the gradient, $\mathrm{TV(u)} = \int_\Omega |\nabla \mathrm{u}|_2$

More precisely, the regularization model is based on the dual formulation of the vectorial Total Variation (VTV) norm and it may be regarded as the vectorial extension of the dual approach defined by Chambolle in [73] for gray-scale/scalar images. The proposed model offers several advantages. First, it minimizes the exact VTV norm whereas standard approaches use a regularized norm. Then, the numerical scheme of minimization is straightforward to implement and finally, the number of iterations to reach the solution is low, which gives a fast regularization algorithm. Finally, and maybe more importantly, the proposed VTV minimization scheme can be easily extended to many standard applications. We apply this L1 vectorial regularization algorithm to the following problems: color inverse scale space, color denoising with the chromaticity-brightness color representation, color image inpainting, color wavelet shrinkage, color image decomposition, color image deblurring, and color denoising on manifolds. Generally speaking, this VTV minimization scheme can be used in problems that required vector field (color, other feature vector) regularization while preserving discontinuities.

The VTV minimization algorithm is fast, easy to code and well-posed. In fact, this vectorial regularization scheme can be applied to any problems that require a L1 regularization process for vectorial components.

VTV minimization model is based on the dual formulation of the vectorial TV norm. Let us consider a vectorial (or M-dimensional or multichannel) function u, such as a color image or a vector field, defined on a bounded open domain $\Omega \subset \mathrm{R}^N$ as

$x \rightarrow u(x) := (u1(x), ..., u_M(x)),\ u : \rightarrow \mathrm{R}^M,$

$$\inf_{u} \ \sup_{|p| \leq 1} \left\{ < u, \nabla . p > \ \mathrm{L}^2(\Omega, \mathbb{R}^\mathrm{M}) + \frac{1}{2\lambda} \|\mathrm{f} - \mathrm{u}\|^2 \Omega; \mathbb{R}^\mathrm{M} \right\} \quad (3.1)$$

Which is convex in u and concave in p and the set {|p|<=1} is bounded and convex.

IV. METHOD OF SIMULATION

The simulation is carried on colored images in MATLAB. To do so different types of noise (Gaussian Noise, Salt & Pepper Noise, Salt & Pepper Noise & Poisson Noise) varying from 1% to 9% is incorporated into image. Each degraded image is denoised by filters. To make a comparative study, analysis is done on four parameters namely:

- Mean

$$\mathrm{MEAN} = \frac{1}{n_x n_y} \cdot \sum_0^{n_y - 1} \ \sum_0^{n_y - 1} r(x, y) \quad (4.1)$$

- Mean Square Error (MSE)

$$\mathrm{MSE} = \frac{1}{n_x n_y} \cdot \sum_0^{n_x - 1} \ \sum_0^{n_y - 1} \ [r(x, y) - t(x, y)]^2 \quad (4.2)$$

- Signal to Noise Ratio (SNR)

$$\mathrm{SNR} = 10.\log_{10}\left[\frac{\sum_0^{\mathrm{n_x}-1}\sum_0^{\mathrm{n_y}-1}[\mathrm{r(x,y)}]^2}{\sum_0^{\mathrm{n_x}-1}\sum_0^{\mathrm{n_y}-1}[\mathrm{r(x,y)}-\mathrm{t(x,y)}]^2}\right] \quad (4.3)$$

- Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10.\log_{10}\left[\frac{max(r(x,y))^2}{\frac{1}{n_x . n_y} . \sum_0^{n_x - 1}\sum_0^{n_y - 1}[r(x,y) - t(x,y)]^2}\right] \quad (4.4)$$

V. ALGORITHM

dual_vectorial_ROF(Im,map)

1. Read Input Image Im.
2. [Ny,Nx,Nc] = size(Im);
3. Im = double(Im);
4. Im = 255* Im/ max(max(Im(:)));
5. dt = 1/8;
6. lambda = 1e1*6;
7. pxU = zeros(size(Im));
8. pyU = zeros(size(Im));
9. U = zeros(size(Im));
10. Denom = zeros(size(Im));
11. nb_iters = 500
12. repeat for cpt=1:nb_iters
13. Divp = (BackwardX(pxU) + BackwardY(pyU));
14. Term = Divp -Im/ lambda;
15. Term1 = ForwardX(Term);
16. Term2 = ForwardY(Term);
17. Norm = sqrt(sum(Term1.^2 + Term2.^2,3));
18. Denom(:,:,1)=1+dt*Norm;
19. Denom(:,:,2)=Denom(:,:,1);
20. Denom(:,:,3)=Denom(:,:,1);
21. pxU = (pxU+dt*Term1)./Denom;

```
22.         pyU = (pyU+dt*Term2)./Denom;
23.         U = Im - lambda* Divp;
24.         T=uint8(U);
25.    end
```

BackwardX(v)

1. [Ny,Nx,Nc] = size(v);
2. dx = v;
3. dx(2:Ny-1,2:Nx-1,:)=(v(2:Ny-1,2:Nx-1,:) - v(2:Ny-1,1:Nx-2,:));
4. dx(:,Nx,:) = -v(:,Nx-1,:);
5. return dx;

BackwardY(v,dy);

1. [Ny,Nx,Nc] = size(v);
2. dy = v;
3. dy(2:Ny-1,2:Nx-1,:)=(v(2:Ny-1,2:Nx-1,:) - v(1:Ny-2,2:Nx-1,:));
4. dy(Ny,:,:) = -v(Ny-1,:,:);
5. return dy

ForwardX(v,dx);

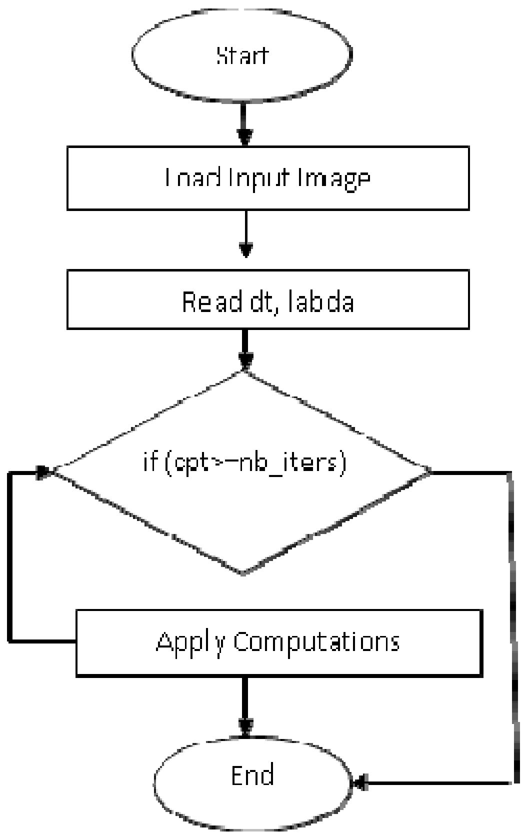
1. [Ny,Nx,Nc] = size(v);
2. dx = zeros(size(v));
3. dx(1:Ny-1,1:Nx-1,:)=(v(1:Ny-1,2:Nx,:) - v(1:Ny-1,1:Nx-1,:));
4. return dx

ForwardY(v,dy)

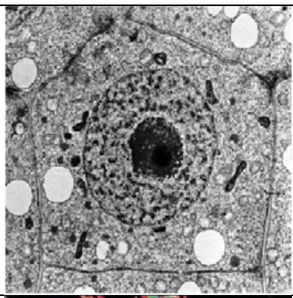
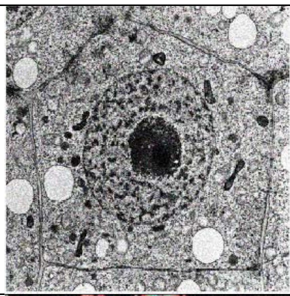
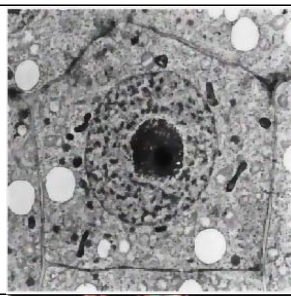
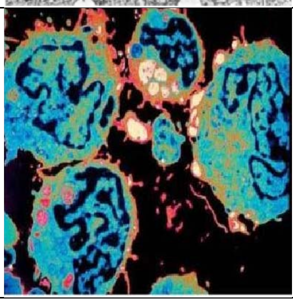
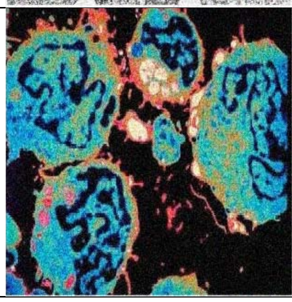
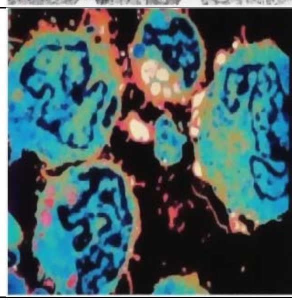
1. [Ny,Nx,Nc] = size(v);
2. dy = zeros(size(v));
3. dy(1:Ny-1,1:Nx-1,:)=(v(2:Ny,1:Nx-1,:) - v(1:Ny-1,1:Nx-1,:));
4. Return dy

This algorithm reads an input image Im. It finds in Line 2, the size of an image, number of rows in Ny, number of columns in Nx, and number of channels in Nc respectively. In line 3 , the image is casted into double so when normalizing on division it does not get zero. Then, in line 4, the pixel intensity range is made from 0 to 255 multiplying the image by 255/(largest pixel value in image). For example, if the intensity range of the image is 0 to 180 and the desired range is 0 to 255. Then each pixel intensity is multiplied by 255/180, making the range 0 to 255. In line 5, the temporal bound (dt) is set to 1/8. It is mathematically proved that this value aids in finding the minimized solution. The temporal bound does not depend on the number of channels. The lambda is set to 1e1*6 in line 6. Four new arrays pxU, pyU, U, Denom of the same size as of input image consisting of all zeros are created in line 7 to 10 respectively. To get a steady state solution the process is repeated several times. These iterations may vary depending upon the noise level. For higher noise levels, more number of iterations are needed. This iteration is set in line11. For each iteration, the below mentioned procedure is applied. It begins by applying the discrete divergence operator in line 13.To do so , it applies two sub-procedures, BackwardX and BackwardY. These sub-procedures, returns a temporary array which is calculated by calculating the consecutive differences of certain elements in the input arrays. The results from these sub-procedures are added to give the divergence operator in line 13. Now a new array Term is calculated by modifying the divergence operator using the input image array and the factor lambda in line 14. Two new arrays Term1 and Term2 are created using the subprocedures ForwardXand ForwardYin Line 15 and 16 respectively. These sub-procedures, returns a temporary array which is calculated by calculating the consecutive differences of certain elements in the input arrays. Now in line 17, Term1 and Term2 are normalized. In image processing, normalization is a process that changes the range of pixel intensity values. In line 18-20, the algorithm introduces coupling between the channels. Each channel use information coming from other channels to improve the denoising model. To convey the information from one channel to another the RGB image is split into three separate greyscale images representing the red, green and blue color planes. The arrays pxU and pyU are then updated in line 21 and 22 with the new values using the information conveyed by each channel mentioned in above lines. The coupling term basically helps to better restore parts in the images where the intensities are weak. Then in line 23, the Euler-Lagrange's technique is used by which the minimized solution of the VROF model is found. The image Is casted to an uint8 data type. The procedure is repeated number of times specified in Line 11 depending upon the noise levels.

VI. FLOWCHART



VII. PICTORIAL RESULTS

DUAL VECTORIAL ROF FILTER			
	Original Image	**Noisy Image**	**Filtered Image**
Greyscale Normal Image			
Greyscale Colored Image			
Greyscale TEM Image			
Colored TEM Image			

VIII. EXPERIMENTAL RESULTS

Gaussian Noise				
Noise Intensity	Mean	MSE	SNR	PSNR
0.001	**169.5292**	8.15E+01	13.3706	29.0184
0.002	**169.7034**	8.22E+01	13.3532	28.9795
0.003	**169.758**	8.28E+01	13.3396	28.9513
0.004	**169.862**	8.41E+01	13.3071	28.8847
0.005	**169.862**	9.26E+03	3.5332	8.4657
0.006	**199.5159**	8.45E+01	13.2982	28.8616
0.007	**170.0708**	8.47E+01	13.2945	28.8533
0.008	**170.1431**	8.58E+01	13.267	28.7952
0.009	**170.3542**	8.70E+01	13.239	28.7372

Speckle Noise				
Noise Intensity	Mean	MSE	SNR	PSNR
0.001	**167.7624**	4.19E+01	14.8123	31.9085
0.002	**167.7638**	4.23E+01	14.7899	31.8637
0.003	**167.7537**	4.29E+01	14.7621	31.8087
0.004	**167.7281**	4.34E+01	14.7335	31.7523
0.005	**167.7441**	4.36E+01	14.7256	31.7361
0.006	**167.7083**	4.42E+01	14.6937	31.6737
0.007	**167.73**	4.47E+01	14.6699	31.6252
0.008	**167.734**	4.50E+01	14.659	31.6033
0.009	**167.7332**	4.53E+01	14.6443	31.5738

Salt & Pepper Noise				
Noise Intensity	Mean	MSE	SNR	PSNR
0.001	**167.8161**	4.29E+01	14.7635	31.8104
0.002	**167.8601**	4.48E+01	14.666	31.6152
0.003	**167.9063**	4.71E+01	14.5586	31.4004
0.004	**167.9316**	4.88E+01	14.4836	31.2504
0.005	**168.0065**	5.19E+01	14.3495	30.9817
0.006	**168.0221**	5.31E+01	14.299	30.8808
0.007	**168.0618**	5.42E+01	14.2556	30.7937
0.008	**168.1104**	5.79E+01	14.111	30.5047
0.009	**168.1394**	6.03E+01	14.0231	30.3292

Poisson Noise	Mean	MSE	SNR	PSNR
Dual Vectorial ROF Filter	**167.7725**	**44.4024**	**14.6864**	**31.6567**

VIII. CONCLUSION

It is clearly visible that DVROFT filter is quite effective for denoising the images both in case of greyscale TEM and colored TEM image with the exception of gaussian noise It is observed that the SNR and PSNR ratios obtained for TEM image is much higher than those obtained for normal image. Also, though DVROFT retains the structure in the image but do not capture very fine details due to smoothing.

REFERENCES

[1] L.I. Rudin, S. Osher, and E. Fatemi, “Nonlinear total variation based noise removal algorithms,” Physica D, Vol. 60, pp. 259–268, 1992.

[2] Antonin Chambolle, Pierre-Louis Lions, “Image recovery via total variation minimization and related problems”, Numer. Math. (1997) 76: 167–188.

[3] S. Roques, K. Bouyoucef, L. Touzillier, J. Vignea, “Prior knowledge and multiscaling in statistical estimation of signal-to-noise ratio — Application to deconvolution regularization”, Signal Processing, Volume 41, Issue 3, February 1995, Pages 395-401.

[4] A. Chambolle. An Algorithm for Total Variation Minimization and Applications. Journal of Mathematical Imaging and Vision, 20(1-2):89–97, 2004.

[5] E. Sekko, G. Thomas, A. Boukrouche, “A deconvolution technique using optimal Wiener filtering and regularization”, Signal Processing, Volume 72, Issue 1, 4 January 1999, Pages 23-32.

[6] J. Darbon and M. Sigelle. Image Restoration with Discrete Constrained Total Variation Part I: Fast and Exact Optimization. Journal of Mathematical Imaging and Vision, 26(3):277–291, 2006.

[7] J. Darbon and S. Peyronnet. A Vectorial Self-Dual Morphological Filter based on Total Variation Minimization. In International Symposium on Visual Computing (ISVC), volume 3804, pages 388–395, 2005.

[8] X. Bresson , T. F. Chan, “Fast Dual Minimizaton of the Vectoral Total Variation Norm & applications to Color Image Processing ”, 2008, CAM Reports, UCLA Department of Mathematics.

[9] Paul Rodriguez, “A Non-Negative Quadratic Programming Approach to Minimize the Generalized Vector-Valued Total Variation Functional”, 18th European Signal Processing Conference (EUSIPCO-2010), Aalborg, Denmark, August 23-27, 2010.

[10] Xiaojuan Gu, Li Gao, “A new method for parameter estimation of edge-preserving regularization in image restoration”, Journal of Computational and Applied Mathematics, Volume 225, Issue 2, 15 March 2009, Pages 478-486.

[11] Vincent Michel, Alexandre Gramfort, Gaël Varoquaux, Evelyn Eger, Bertrand Thirion , “Total variation regularization for fMRI-based prediction of behaviour”, Computer Vision and Pattern Recognition , IEEE Transactions on Medical Imaging (2011).

[12] Antigoni Panagiotopoulou, Vassilis Anastassopoulos, “Super-resolution image reconstruction techniques: Trade-offs between the data-fidelity and regularization terms”, Information Fusion, Volume 13, Issue 3, July 2012, Pages 185-195.