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Improved Image Denoising Filter using Low Rank & Total Variation

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Abstract- Better diagnosis of disease is possible only with the better microscopic images. To do so images of the affected area are captured and then noise is removed to obtain accurate diagnosis. Many algorithms have been proposed till date. But they are capable of removing noise only in spatial domains so this paper tries to overcome that by combining low rank filter and regularization. If we only reduce noise in spatial or spectral domain, artefacts or distortions will be introduced in other domains. At the same time, this kind of methods will destroy the correlation in spatial or spectral domain. Spatial and spectral information should be considered jointly to remove the noise efficiently. Low rank algorithms are good as they encloses semantic information as well as poses strong identification capability.

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Improved Image Denoising Filter using Low Rank & Total Variation

Garima Goyal

Abstract- Better diagnosis of disease is possible only with the better microscopic images. To do so images of the affected area are captured and then noise is removed to obtain accurate diagnosis. Many algorithms have been proposed till date. But they are capable of removing noise only in spatial domains so this paper tries to overcome that by combining low rank filter and regularization. If we only reduce noise in spatial or spectral domain, artefacts or distortions will be introduced in other domains. At the same time, this kind of methods will destroy the correlation in spatial or spectral domain. Spatial and spectral information should be considered jointly to remove the noise efficiently. Low rank algorithms are good as they encloses semantic information as well as poses strong identification capability.

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I. Introduction

The transmission electron microscope (TEM) is used to examine the structure, composition, and properties of specimens in submicron detail. Aside from using it to study general biological and medical materials, transmission electron microscopy has a significant impact on fields such as: materials science, geology, environmental science, among others.Various TEM image denoising algorithms have been proposed in the recent years [1][2][3][4]. At a maximum potential magnification of 1 nanometer, TEMs are the most powerful microscopes. TEMs produce high-resolution, two-dimensional images, allowing for a wide range of educational, science and industry applications.

All the algorithms remove the noise in only in spatial domain which in turn deteriorate correlation in spectral domain. Highly correlated images set have the nature of low rank; they can be recovered efficiently from measurement with noise or outliers by using the restriction of low rank [5][6][7]. While sparse coding and dictionary learning a error was introduced which can be reduced by imposing a low rank algorithm. To make the problem solvable total variation, i.e regularization will be used.

II. Literature Survey

Low rank approximation is good for recovering low dimensional structures in data. It is been in use in variety of applications in image and video processing. A new denoising algorithm based on iterative low-rank regularized collaborative filtering of image patches under a nonlocal framework. This collaborative filtering is formulated as recovery of low rank matrices from noisy data. Based on recent results from random matrix theory, an optimal singular value shrinkage operator is applied to efficiently solve this problem [8]. A sparse banded low pass filter is discussed which showed significant improvement in PSNR [9]. A combined denoising strategy, and adaptive dimensionality reduction approach of similar patch groups by parallel analysis was used which indicated appropriate results [10]. A image Deblurring using split bergman iterative algorithm was proposed characterizing both image local smoothness and non local self similarity [11].

III. Algorithm

It solves following optimization problem

min_X || Y-X||_1 + lambda ||Dh*X||_1 + lamdba ||Dv*X||_1 + mu ||X||_* (3.1)

Here in this equation, X is the Input TEM image, Y indicates the Noisy image, Dh & Dv are the horizontal and vertical finite difference operators, ||X||_* means the Nuclear norm of matrix X. We utilize split-Bregman technique to solve above problem. Before running the algorithm we set the mu(1), mu(2), mu(3) which corresponds to total variation term, low rank term and data fidelity term respectively.

1. img=imread('ctem.jpg');
2. img=im2double(img);
3. [rows,cols,d]=size(img);
4. sizex=[rows,cols];
5. noisy = imnoise(img,'salt & pepper',0.02);
6. psnrBefore=findPSNR(img,noisy,1);
7. y=reshape(noisy,rows*cols,d);
8. mu=[.2 .2 .5]; iter=10;
9. x=basicDenoising(y,sizex,mu,iter);
10. psnrRec=findPSNR(img,x,1);
11. bands=[1 floor(d/2) d]; %these are the bands to be displayed
12. img=myhisteq(img);rec=myhisteq(x); noisy=myhisteq(noisy);
13. subplot(131); imshow(img(:,:,bands)); title('Original Image');

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```
14. subplot(132); imshow(noisy(:,:,bands)); title('Noisy
    Image');
15. subplot(133); imshow(rec(:,:,bands));
    title('Reconstructed Image');
function x = basicDenoising(y,sizex,mu,maxiter)
1.  mu1=mu(1) ; mu2=mu(2); mu3=mu(3) ;
2.  [~,d]=size(y);rows=sizex(1);cols=sizex(2);
3.  B1=zeros(rows*cols,d); B2=B1; B3=B1; B4=B1;
4.  [Dh,Dv]=TVR(rows,cols);
5.  x=zeros(rows*cols,d);
6.  for i=1:maxiter
P=Sfth(Dh*x+B1,1/mu1);
                Q=Sfth(Dv*x+B2,1/mu1);
                R=Nnth(x+B3,1/mu2);
                S=Sfth(y-x+B4,1/mu3);

                bigY=Dh'*(mu1*(P-
B1))+Dv'*(mu1*(Q-B2))+mu2*(R-B3)+mu3*(y-S+B4);

                for j=1:d

                [x(:,j),~]=lsqr(@find,bigY(:,j),1e-
6,5,[],[],x(:,j));
                end
                B1=B1+Dh*x-P;
                B2=B2+Dv*x-Q;
                B3=B3+x-R;
                B4=B4+y-S-x;
                if rem(i,2)==0
                     fprintf(' %d iteration done of %d
\n',i, maxiter);
                end

end
7.  x=reshape(x,rows,cols,d);
end
 function y = find(x,str)
1.  tt= mu1*(Dh'*(Dh*x))+ mu1*(Dv'*(Dv*x))+ mu2*x
    + mu3*x;
2.  switch str
case 'transp'
y = tt;
     case 'notransp'
                y = tt;
   end
end
function X= Sfth(B,lambda)
1.  X=sign(B).*max(0,abs(B)-(lambda/2));
end
function X=Nnth(X,lambda)
1.  if isnan(lambda)
                lambda=0;
end
2.  [u,s,v]= svd(X,0);
3.  s1=Sfth(diag(s),lambda);
4.  X=u*diag(s1)*v';
end
```

```
function [Dh, Dv]=TVR(m,n)
1.  Dh = spdiags([-ones(n,1) ones(n,1)],[0 1],n,n);
2.  Dh(n,:) = 0;
3.  Dh = kron(Dh,speye(m));
4.  Dv = spdiags([-ones(m,1) ones(m,1)],[0 1],m,m);
5.  Dv(m,:) = 0;
6.  Dv = kron(speye(n),Dv);
end
```

IV. Results

The algorithm is implemented in MATLAB. A nanoscopic TEM is taken and salt & pepper noise is added. Then the filter is applied to denoise the image. Peak Signal to noise ratio is evaluated before and after applying the filter. One sample result is indicated below.
PSNR before denoising : 14.92
PSNR after denoising : 27.87

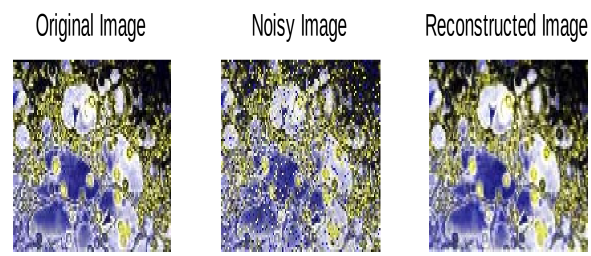

Figure 4.1 : Results before and after applying the Filter

V. Conclusion

By introducing ideal regularization term and performing low rank matrix recovery we are able to denoise image successfully without losing structural information. The peak signal to noise ratio obtained is significantly much higher and quite significant.

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