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RESEARCH ARTICLE

The Effect of Lambda in Recovering the Highly Corrupted Image using Adaptive Directional Lifting Induced Proximal Gradient Method

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ABSTRACT

Image completion have the many real time applications in machine learning, compressed sensing etc., The image with more than 80 percent lost information are solved using image completion algorithms. The applications are made the researchers to work and develop the Image completion algorithms. The transform-based optimization methods are able to recover the corrupted images more clearly. Here a new algorithm named Adaptive Directional Lifting Wavelet Transform (ADLWT) based regularizer has been introduced. It is able to recover the image at high corruption ratios. The ADLWT is predicts the corrupted values depending on the directions in such a way that perfectly matches. It is induced with the optimization method named Accelerated Proximal Gradient Line (APGL). The proposed algorithm is evaluated with the Full-Reference Image Quality Assessment (FRIQA) and No-Reference Image Quality Assessment (NRIQA) metrics. The results are improved with respect to image quality and structure information. The impact of lambda in the optimization and the optimal value is identified.

Keywords: Adaptive Directional Lifting, Optimization, ADL Regularizer, Directional Wavelets, Transform based optimization

INTRODUCTION

Wavelet transforms are playing a vital role in the Image and Video processing applications. The multi resolution, energy compaction and spacio–frequency localization are the factors lead to use in many real time applications. Most of the images have the energy in low frequency bands, so decomposition is very effective in image processing, computer vision and compressed sensing applications. The conventional lifting wavelet transform is performing the filtering, in horizontal and vertical directions. The information present in the image can be identified with this operation, but that information is predicted based on horizontal and vertical operations. The diagonal information among the pixels is missing, it leads to loss of structural information in the reconstruction image. This drawback is can be overcome by Adaptive Directional Lifting Wavelet Transform [1-3]. It is able to predict the pixels values with diagonal operations as similar to horizontal/vertical operations in adaptive lifting.

The ADLWT determines the corrupted pixel value by utilizing the interpolated information between pixels. The interpolated information is 1/4 and 1/2 value of the neighboring pixels. Based on the angle, the comparison of neighborhood pixel value is considered [2]. At which position the difference is small that value will be considered and it will be replaced. The process requires several transformations in each pixel. Hence the computational consists is much higher than the traditional wavelet transform. If the image lost there details more the regular transform-based coding methods are alone not sufficient. The optimization approach is very essential in recovering the missing pixels in the corrupted image. The rank minimization algorithms are also proposed to recover the highly corrupted images. But the transform-based approaches are recovering more efficiently. So here the ADLWT is introduced with the Accelerated Proximal Gradient Line (APGL) optimization. It recovers the corrupted image in less time because the APGL is fast in computations.
The main contribution of the work are as follows

- An efficient Adaptive Directional Lifting based APGL approach has been introduced to improve diagonal correlation among the pixels.
- The interpolation method has been introduced to identify the diagonal relation between pixels. Then the predicted pixels are updated.
- The proposed method has been evaluated using FRIQA and NRIQA measures. The results are stating that the proposed method is recovering the highly corrupted image.

The paper has been organized as section 1 gives literature review on Image Completion methods. The previous works done are discussed, in Section 2 drafted with the earlier work done by various authors. Section 3 is provided with detail explanation of the ADL based optimization method to solve the optimization function. In section 4 presented the results on various recovered images. Finally, section 5 gives the conclusion on proposed method.

Literature Review

Image Completion is having the wide application scope in Machine Learning, Compressed Sensing and Computer Vision applications. The image completion is performed with the highly corrupted images. The conventional denoising algorithms are able to eliminate the noise in less corrupted images. The wavelets are playing a vital role in the denoising of an image. Recent years fully exploiting the directional correlation in either spatial or frequency domain with the directional filter banks. Most of the decomposition methods are become expensive systems and difficult for the applications, Daubechies et al., proposed lifting wavelet. It reduces the computational complexity of conventional wavelet transform. Adaptive directional lifting wavelet transform incorporates the local spatial prediction into each lifting step [4, 5]. The direct applying of ADL may lead of some artifacts in the recovered image.
The major problem in directional prediction with wavelet decomposition makes the conflict of global and local features. To eliminate the noise in highly corrupted images denoising methods are not sufficient. To get better quality in the image both denoising method and optimization need to be combined. The Singular Value Thresholding (SVT) is the most familiar method developed by E.J. Candes et al. [6]. The basic optimization function is formed as

$$\min_I \|I\|_* + \alpha\|I\|_F^2 \qquad \textit{Subject to } P_\Omega(I) = P_\Omega(R) \qquad (1)$$

The eq. 1 is solved by the Uzawa method and solves efficiently. But the missing ratio in the image getting increase the existing methods are unable to recover. So a transformation based optimization need to introduced to recover the highly corrupted images. Y. Hu et al. [7] proposed rank minimization method which is able to recover better than the

SVT. The proposed algorithm is based on the rank, as the minimal rank is considered the recovered image will have the good measures. If the missing ratio in the image is increasing, the given method alone unable to recover the data. The objective function is formed as in eq.2

$$\min_I \|I\|_r + \alpha\|I\|_F^2 \qquad \mathit{Subject\ to}\ P_\Omega(I) = P_\Omega(R) \tag{2}$$

Wang Y et al. [8] proposed a transform-based optimization method which is used the TNNR as the special condition and achieved the good recovery of the image. The objective function is defined as

$$\hat{X} = arg\min_I \|I\|_* + \sum_{i=1}^{s}\lambda_i\|I\|_{DCT}^{p_i,q_i} + \frac{\gamma}{2}\|P_\Omega(I) - P_\Omega(R)\|_F^2 \tag{3}$$

Jing dong et al [9], proposed a low rank based matrix completion induced with Discrete Cosine Transform (DCT). It recovers the image with high PSNR and high SSIM. Kumar J S et al. [10] proposed the method lifting based optimization named LwRM regularizer is able to recover the highly corrupted image. The problem is defined as in eq. 4

$$\hat{I} = \arg min\,\|I\|_* + \lambda\|I\|_{LWT} + \frac{\gamma}{2}\|\mathcal{P}_\Omega(I) - \mathcal{P}_\Omega(R)\|_F^2 \tag{4}$$

They proposed with the most familiar gradient-based optimization. Here is used with the adaptive lifting wavelet transform. Nestrov [11] proposed an optimization method which has the fast convergence rate with less computational complexity. Here the Adaptive Directional Lifting is combined with the gradient descent-based optimization. The introduced method is evaluated with the most familiar metrics PSNR [12], SSIM [12], and NIQE [13]. The results are enclosed in section 5 and discussed in-detail.

ADLWT Regularizer

Here we are proposing a transform-based optimization method which can recovers the highly corrupted image. The adaptive directional lifting wavelet transform is used, because the corrupted pixel values are identified with help of directionally identified uncorrupted pixel values.

Adaptive Directional Lifting (ADL) Wavelet Transform

The Adaptive Lifting Wavelet performs the operations in horizontal and vertical directions. The Adaptive Directional Lifting is not limited to the horizontal and vertical directions the diagonal operation will be performed by considering the angle. The basic adaptive directional lifting performs the split, predict, update and normalize operations. It provides the sub-pixel perfect and accurate reconstruction of corrupted pixel value. The prediction of each is a linear combination of neighboring even coefficients with strong correlation in the concern directions. A high angular resolution in prediction is achieved by the use of the fractional pixels in prediction and update steps. An interpolation operation is attached to the prediction and update steps in the ADL scheme. The fig. 1 shows the sample directions of finding the pixels in different directions.

$X_e(m, n) = X(m, 2n)$

$X_o(m,n) = X(m,2n+1)$

$P_e[m,n] = \sum_i p_i x_e^*[m+i, n+sign(i-1)*dir]$

$U_d[m,n] = \sum_i u_i d^*\ [m+i, n+sign(i-1)*dir]$ (5)

P_e represents the lifting coefficient for prediction step and U_d represents the updation coefficients. Update process to replaces the pixel values identified using eq. 5. Every pixel/block have the transform direction the direction yielding the smallest high frequency energy is considered as transform direction. By using interpolation method, the effective direction will be calculated and with that updation will be done.

The SVD has been applied transformed image regions separately, then the unitary matrices and singular values are used in the optimization function as variables.

APGL Optimization Process

The optimization function can be described as eq. 6 and it is solved using the accelerated proximal gradient line method.

$$\hat{I} = arg\min_I \|I\|_* + \lambda\|I\|_{ADL} + \frac{\gamma}{2}\|\mathcal{P}_\Omega(I) - \mathcal{P}_\Omega(R)\|_F^2 \quad (6)$$

Update I_{k+1}:

$$I_{k+1} = \arg\min\|I\|_* + \frac{1}{2t}\|I - (I_k - t_k.\nabla f(I_k)\|_F^2 \quad (7)$$

Equation (21) can be solved using $U^T SV = I_k - t_k.\nabla f(I_k)$ and $= \max((S_i - t_k), 0)$

Updatet_{k+1}:

$$t_{k+1} = \frac{1+\sqrt{1+4t_k^2}}{2} \quad (8)$$

Update R_{k+1}:

$$R_{k+1} = I_{k+1} + \frac{t_k - 1}{t_{k+1}}(I_{k+1} - I_k) \quad (9)$$

Algorithm

- Input: observed set *I, R*
- Initialization: The recovered Image *M=I, λ.*
- Apply the Adaptive Direction Lifting on each layer of the image then calculate the SVD of I_l
- Compute A_l and B_l from uniform matrix obtained from SVD
- Solve the following constrained optimization problem
- Until $\|I_{l+1} - I_l\|_F \leq 0.001$ if condition gets satisfied stop the iteration otherwise continue the iteration.

RESULTS AND DISCUSSION

The proposed ADLWRM is tested with the bench mark images [14]. The recovered images are evaluated with various image quality assessment metrics. The full reference image quality assessment metrics MSE, PSNR, and SSIM. The No-reference image quality assessment metric NIQE. The recovered results for the pepper image are shown in fig. 2. It clearly says that the recovery of the corrupted image has the best visual quality at λ=0.01 using the adaptive directional lifting scheme. Fig. 3 shows PSNR and SSIM of Pepper image recovered with different corrupted ratios and with different lambda values. The lambda value is 0.0001 the PSNR is more to recovered image with 10 % uncorrupted samples, but the SSIM value is very minimal. Because to the minimal lambda value the objective function is reaching the convergence faster and without recovering the corrupted observations it is reaching the stop condition. If we increase the number of iterations also it is providing the same result. To the lambda value 0.01 the PSNR and the SSIM values are providing the better results. Similarly, the NRIQA measure NIQE also minimal value for the lambda (0.01) as shown in fig. 4 (a). In fig. 4 (b) shows the time taken to recover the corrupted images with different stages. It varies from 10 % to 90% uncorrupted observations vs the time taken with different lambda values. The Tab.1(a) to (d) shows the numerical values of FRIQA (MSE, PSNR and SSIM) and NRIQA (NIQE) metrics for different missing ratios. Fig. 5 (a) to (d) shows the comparison graphs for the provided tables. The plotted graphs are clearly giving the hypothesis that the lambda value is the very important parameter in recovering the highly corrupted image.

CONCLUSION

The proposed ADLWT Regularizer is able to direct the subpixel position edge detail of the image properly with adaptive direction. In every stage of the missing ratio the proposed method can guaranteed the perfect recovery. To improve the efficiency of the method the optimization is combined, so it can be easily address image acquisition problems in the machine learning. The gradient method the ◎ is played a crucial role and the optimal value identified as 0.01. The FRIQA metrics PSNR, and SSIM are reported as 30.22dB and 0.8451 respectively to 80% corrupted image. Similarly, for the NRIQA metric NIQE as 9.52 and time taken to recover the corrupted image is 14.34 sec.

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Tab. 1 (a) Peak Signal to Noise Ratio vs Missing Ratio

Missing Ratio/ Lambda Value	10.00	20.00	30.00	40.00	50.00	50.00	70.00	80.00	90.00
0.0001	31.74	31.63	31.51	31.31	31.07	30.79	30.32	29.68	34.49
0.001	43.30	40.18	37.96	36.07	34.48	33.10	31.74	30.32	28.99
0.05	44.44	40.44	37.94	35.91	34.33	33.27	32.38	31.55	30.65
0.01	44.53	40.58	38.14	36.14	34.51	33.06	31.61	30.22	29.13
0.1	44.55	39.89	37.44	35.41	34.72	33.81	33.18	32.40	31.67

Tab. 1 (b) Structural Similarity for various lambda values

Missing Ratio/Lambda Value	10.00	20.00	30.00	40.00	50.00	60.00	70.00	80.00	90.00
0.0001	0.9517	0.9482	0.9433	0.9375	0.9286	0.9153	0.8935	0.8484	0.4025
0.001	0.9974	0.9939	0.9884	0.9797	0.9662	0.9477	0.9178	0.8617	0.7226
0.05	0.9978	0.9940	0.9866	0.9721	0.8940	0.7553	0.6264	0.4796	0.3394
0.01	0.9979	0.9943	0.9886	0.9798	0.9662	0.9469	0.9135	0.8451	0.6201
0.1	0.8693	0.7416	0.6354	0.6108	0.6738	0.5674	0.4734	0.3684	0.2769

Tab. 1 (c) NIQE for various lambda values

Missing Ratio/Lambda Value	10.00	20.00	30.00	40.00	50.00	50.00	70.00	80.00	90.00
0.0001	6.47	6.33	7.18	7.23	8.05	8.36	9.81	13.10	12.18
0.001	3.26	3.41	3.54	4.39	4.71	5.67	7.05	10.56	16.39
0.05	3.39	3.63	3.67	4.50	7.63	15.22	15.90	13.86	11.48
0.01	3.36	3.64	3.71	4.32	4.72	5.70	7.06	9.52	13.66
0.1	24.24	28.30	27.14	26.45	27.23	28.60	27.37	16.07	12.86

Tab. 1 (d) Time taken to recover the image

Missing Ratio/Lambda Value	10.00	20.00	30.00	40.00	50.00	50.00	70.00	80.00	90.00
0.0001	13.40	14.51	14.65	15.84	17.59	18.79	20.97	24.06	10.22
0.001	15.52	15.33	14.93	14.89	15.26	14.37	14.25	14.59	17.10
0.05	10.79	12.89	14.11	14.98	16.47	17.85	19.45	20.39	21.93
0.01	9.97	9.85	10.21	11.52	10.87	11.46	12.38	14.34	18.14
0.1	8.39	8.88	9.37	14.51	21.02	22.56	23.30	24.76	25.20

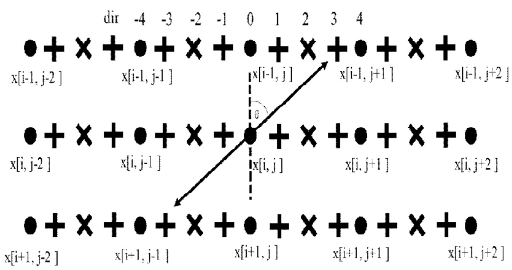


Fig. 1. Direction of sample collection

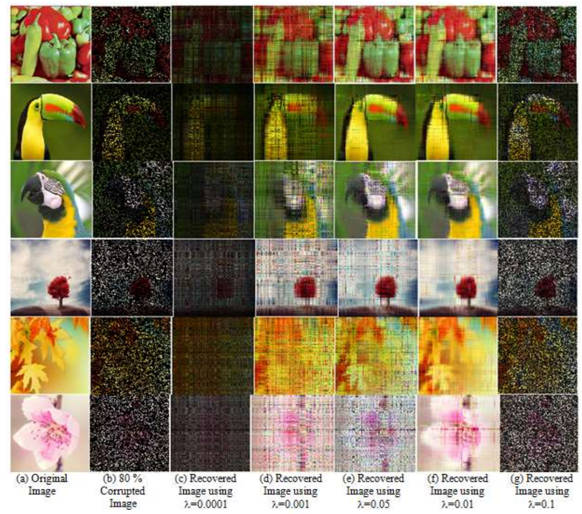
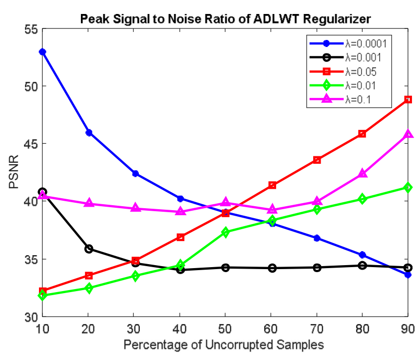
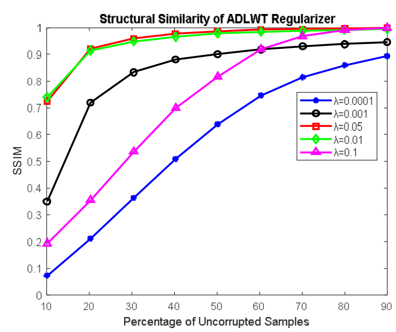


Fig. 2. Sample recovered image from the 80 % corrupted observations with different 'λ' values.

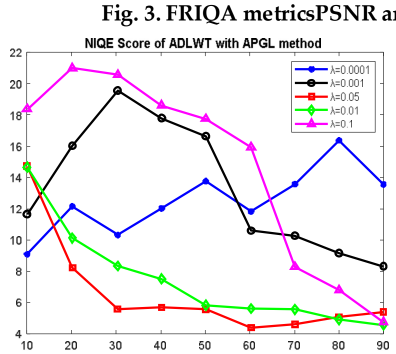


(a) Percentage of Uncorrupted Samples vs PSNR

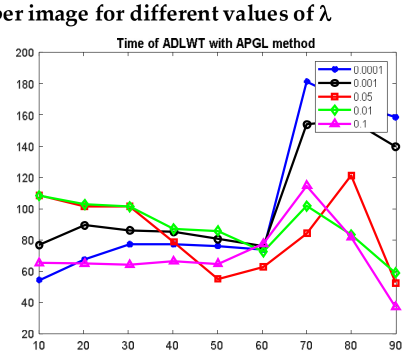


(b) Percentage of Uncorrupted Samples vs SSIM

Fig. 3. FRIQA metricsPSNR and SSIM of Pepper image for different values of λ



(a) Percentage of Uncorrupted Samples vs NIQE



(b) Percentage of Uncorrupted Samples vs time

Fig. 4. NRIQA metric NIQE of Pepper image for different values of λ

Fig. 5 (a) PSNR of Parrot image recovered from different missing ratios and different Lambda values

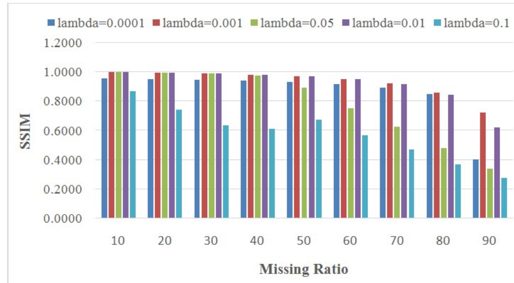


Fig. 5 (b) SSIM of Parrot image recovered from different missing ratios and different Lambda values

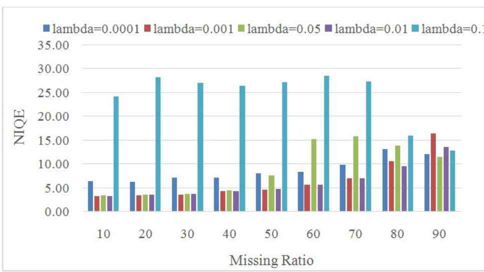


Fig. 5 (c) NIQE of Parrot image recovered from different missing ratios and different Lambda values

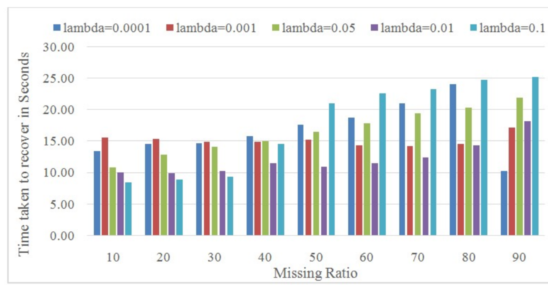


Fig. 5 (d) Time taken to recover parrot image from different missing ratios and different 'λ' values