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An Optimal Selection of Stopping Criteria for Continuous Blind Image Deblurring

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***Abstract*— Blind Image Deblurring (BID) is the processes of recovering original image from the blurred image in the absence of complete or partial details about blur filter and image. It is an ill posed problem that can be solved by utilizing regularization or earlier information, Total Variation regularization based BID is used iteratively to perform denoising and deblurring at the same time. This method require manual stopping of algorithm. Objective of proposed criteria is to stop the continuous blind image deblurring method automatically at reduced number of iterations compare to state-of-the-art method. Rationale of this criterion is comparison of spectral properties of white noise with the residual image. Synthetic experiments are performed on different images. ISNR is used as quality metric to evaluate the quality of results.**

***Index Terms*— Blind Image deblurring, TV Regularization, Residual image, ISNR, White noise.**

I. Introduction

Blur is defined as the degradation of sharpness of the image, causing loss of high frequency components in the image. In image restoration, image deblurring is one of the important problems. It has wide range of applications in many areas like astronomy, photography, medical imaging techniques.

Classification of image deblurring is of two types. They are non-blind image deblurring (NBID) and blind image deblurring (BID). In NBID, blurring filter is assumed to be known. In BID, underlying image and blur kernel are completely (or) partially unknown.

In degradation model of blind image deblurring observed image is represented as the convolution of original image with the filter which is used to blur, followed by some noise. Blind image deblurring is used for accurate estimation of both image & blur kernels which are completely or partially unknown. Blind image deblurring process has infinite number of solutions because of presence of more number of pairs of filter and image estimates. To handle this ill-posed nature of Blind image deblurring can be solved by utilizing regularization. Introducing additional information is known as regularization. Regularization based image deblurring algorithms are iterative nature. This method involves estimation of image and blur filter using total variation regularization. Existing approaches are used for manual stopping of algorithms based on visual assessment or ISNR measurement.

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II. EXISTING METHODS

Existing blind image deblurring methods have made assumptions on blur filters either in a hard way by using parametric models [5], [6] or in soft way by using priors/regularizers [3], [4].

Continuation BID is most recent method used for retrieving underlying image and blur filters using sparsity including regularizers (Total Variation Regularizers). It achieves state-of-the-art performance without using any prior knowledge about the blurring filter. It has iterative nature and the limitation of this method is that it requires manual stopping of algorithm based on visual assessment.

Discrepancy Principle (DP) [7], generalized cross validation (GCV), L-Curve [8], [9], criteria are developed to stop the algorithms based on residual image (which is obtained by removing estimated image from the observed image) this methods utilized statistical properties of residual image i.e., variance, MSE and other residual moments. But, this values available only in the presence of accurate blur estimate. This methods are suitable only for Non Blind Image Deblurring algorithms but not for BID.

To overcome the drawbacks of existing methods and to stop the algorithm at final iteration optimal selection of stopping criteria is proposed. It depends on spectral properties of residual image but not on statistical properties.

III. PROPOSED METHOD

A criterion to stop iterative blind image deblurring method is proposed. The primary principle of this method is that the noise present in the observed image should be white Gaussian noise. It is an assumption in proposed criteria. The rationale of stopping criteria depends on spectral properties of residual image.

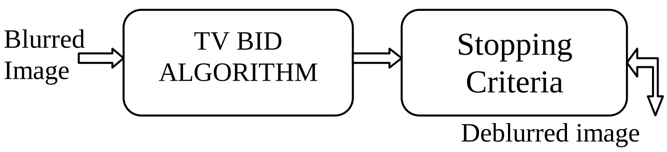


Figure1: Block diagram of proposed method

Proposed method involves Total Variation (TV) BID algorithm which is continuous in nature and stopping criteria which is used to stop the algorithm.

A. TV Blind Image Deblurring Algorithm:

Blind image deblurring is the problem with ill posed behavior. In the degradation model, the image which is blurred is represented as the convolution of clear image with blur kernel followed by some noise.

$$y = h * x + n \tag{1}$$

Where,
y = blurred image
x = (unknown) original image
n = noise
h = point spread function (impulse response of blur filter)
*denotes two dimensional convolution

Goal of Total Variation BID algorithm [1] is to estimate both underlying image and blur filters by minimizing total variation is defined as the integral of absolute gradient of an image. In terms of formula it can be represented as an optimization problem. This problem involves objective function minimization with respect to both image x and blur kernel h. Objective function is represented as

$$C_\lambda(x,h) = \frac{1}{2}\| Y - h * x \|_2^2 + \lambda\phi(x) \tag{2}$$

In the above expression first term is the data fidelity term. It results from the assumption that the noise is white noise. $\phi(x)$ represents prior information about the image and λ is regularization parameter which controls the algorithm. Too large values of λ produce cartoon like images and too small values of λ results under regularized images so, adequate choice of regularization parameter is necessary.

A local minimum of the objective function produce good deblurring results. Alternating direction method of multipliers (ADMM) is used to obtain the local minima of objective function and perform simultaneously both deblurring and denoising. With this approach image and blur filter estimates are obtained. Iterative algorithm is stopped by visual assessment in case of real photos and in case of synthetic experiments ISNR is used to stop the algorithm.

B. Stopping Criteria:

Stopping criteria is used to select the final iteration of TV BID algorithm. It depends on the spectral properties of the residual image. Residual image is obtained by removing estimated image from the observed image

$$r = y - \hat{h} * \hat{x} \tag{3}$$

Spectral properties of residual image are compared with the characteristics of white noise which is assumed in the degradation model. Global and local measures are used to compare residual image and white noise. These are used to measure the whiteness i.e., blur and noise content in the residual image.

C. Whiteness Measures:

Whiteness measures are used to compare the spectral properties of residual image and white noise. Residual image is normalized with mean zero and variance with unity. Normalized residual is represented as r,

$$r \leftarrow \frac{r - \bar{r}}{\sqrt{\mathrm{var}(r)}} \tag{4}$$

White noise is uncorrelated; to compare this with residual image autocorrelation of normalized residual r is calculated by,

$$Rrr(m,n) = k\sum r(i,j)r(i-m, j-n) \tag{5}$$

Autocorrelation of white noise is delta function at the origin. Energy of autocorrelation function is the first measure.

$$M_R(r) = -\sum (Rrr(m,n))^2 \tag{6}$$

Normal process exhibits short range of correlations. To give more weight to autocorrelation for small lags. Then weighted version of first measure is given as,

$$M_{RW}(r) = -\sum W(m,n)(Rrr(m,n))^2 \tag{7}$$

Where, $W(m,n) = \exp(-1.25(m^2 + n^2))$

This is the measure based on the weighted autocorrelation. Power spectral density of residual image is

$$Srr = F(Rrr) \tag{8}$$

Where, F is the magnitude of the two dimensional discrete Fourier Transform. Power spectral density of white noise is flat. Shannon entropy is used to assess the flatness of power spectral density. Measure based on entropy is given as,

$$M_H(r) = -\sum_{w,v} \tilde{S}rr(w,v)\log \tilde{S}rr(w,v) \tag{9}$$

Where,

$$\tilde{S}rr(w,v) = Srr(w,v) / \sum_{w',v'} \tilde{S}rr(w',v')$$

These global measures are computed when the residual r is sample of stationary process. Global measures consider whole image. Practically, residual image not stationary all the time. Local measures are used for the residual of non stationary process. Measures are computed in block-by-block fashion. When the blur filter and images are estimated properly, residual image contain noise and blur details in a large quantity and very little image structure. At this point any one or all of the measures will get maximum value and exhibits clear peak as a function of iteration number. Search scheme is used to select the iteration number as soon as the whiteness starts to decrease.

Stopping criteria also works in the absence of noise. If no noise is added to the degradation model then also residual image contain little spatial structure. Whiteness measures are calculated for this residual image.

IV. QUALITY METRIC

Signal to noise ratio improvement (ISNR) is used to evaluate the quality of results of synthetic experiments and to compare the proposed method with existing method [2]. Units for ISNR is decibels

$$ISNR = 10 \log 10 \frac{\sum_i (y^i - x_0^i)^2}{\sum_i (x^i - x_0^i)^2} \quad (10)$$

Where,
x_0 = original image = signal
y = degraded image
x = recovered image
$(y- x_0)$ = noise of y
$(x- x_0)$ = noise of x

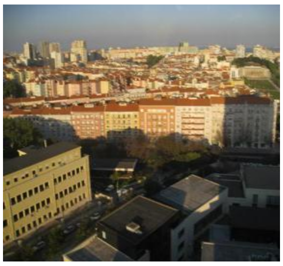
V. SYNTHETIC EXPERIMENTS

Experiments are performed on different images and blur kernels, with or without adding white noise of 40dB BSNR (blurred signal to noise ratio).

Input images used for the experiments are as shown below.


(a)


(b)


(c)


(d)

Figure 2: Input images for synthetic experiments: (a) Lena, (b) Muktha, (c) Buildings, (d) Barbara

Blur kernels used for synthetic experiments are as shown below.

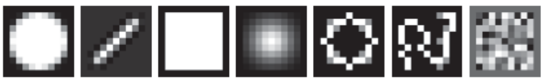

(a) (b) (c) (d) (e) (f) (g)

Figure 3: (a) out-of-focus kernel (b) linear motion filter, (c) kernel with uniform square blur, (d) Gaussian blur kernel, (e) – (f) non linear motion, and (g) random kernels

Different images are applied to continuous blind image deblurring algorithm and the algorithm stopped at the final iteration based on the whiteness measures by spectral properties of residual image. Proposed method is compared with the existing method by ISNR values.

VI. EXPERIMENT RESULTS

Synthetic experiments are performed on Lena image with linear motion blur and with 40dB BSNR of white noise. Experiment results are given below.

Figure 4: image with noise and blur

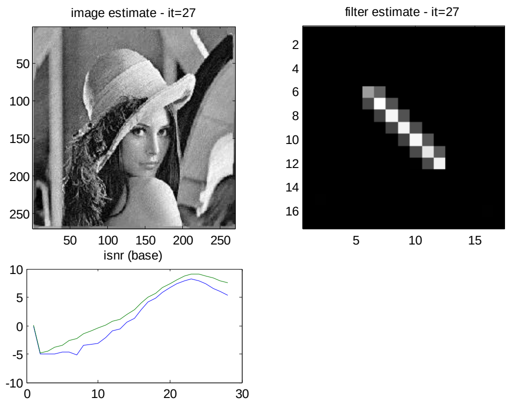


Figure 5: Image & blur filter estimates at each iteration with ISNR measurement

Figure 6: Final image & blur estimates with ISNR measurement in TV BID algorithm

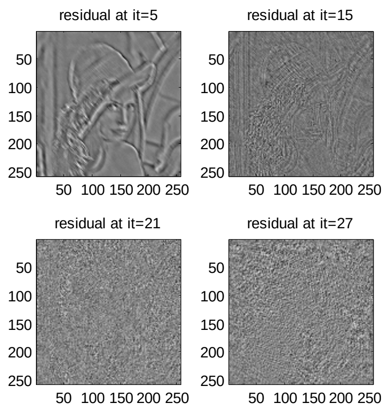


Figure 7: Residual image estimation at each iteration of algorithm

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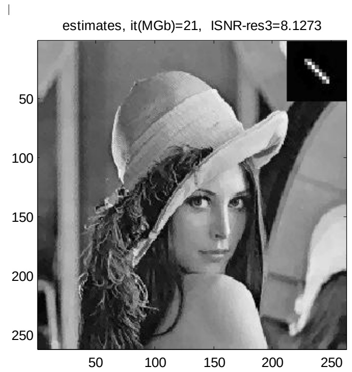

Figure 8: Final image & blur filter estimates based on spectral properties of residual image (stopping criteria)

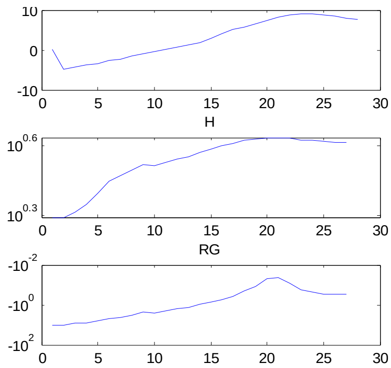

Figure 9: Comparison of ISNR measurement with Whiteness measures with respect number of iterations

VII. CONCLUSION

We have proposed new criteria to stop iterative blind image deblurring algorithms. Rationale of this criterion is based on spectral properties of residual image. Whiteness measures are evaluated for every iteration of continuous blind image deblurring algorithm. At optimal final iteration of algorithm whiteness measures show clear peak. A proposed criterion is applied to various real photos and synthetically degraded images. Results are compared with existing method in terms of ISNR values. We observed that the best of the proposed criteria produce ISNR losses with the respect to the state of the art method ISNR of only 0.5dB, on average. Proposed method is implemented in MATLAB R2013a software.

VIII. FUTURE SCOPE

Total amount of processing time will get decreased by implementing image deblurring algorithms in spatial domain.

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