Image De-Blurring Based on Constraint Conditional Model

Ravikumar H C, P Karthik

Abstract: Image capturing is more vulnerable to the various physical limitations such as defocus, low lighting and camera shaking; this makes the image blurry and noisy. Moreover De-blurring is the process to recover the original image from the given degraded image. De-blurring technique uses the estimated blur kernel for achieving the optimal restored image with the sharp features, however the accuracy has been one of the major concern , hence in this paper we use Constrained Conditional model (CCM) for restoring the image. Moreover, here two different methods are integrated i.e. conditional model and convergence operator, these two combined learns the model and efficiently and provides the better results. In order to evaluate the proposed model, Levin dataset is used by considering the two eminent model metric i.e. PSNR and SSIM and CCM based model outperforms the other state-of-art technique.

Keywords: De-blur, CCM, Image restoration

I.   INTRODUCTION

Image processing has a variety of application such as robotics, scientific imaging, computer graphics, computer vision and computational photography, moreover he traditional approach have been proposed for these applications separately [1]. However after the several years of research the researcher found that the above application share common task which is recovering of the particular image from the indirectly sampled, sparsely, noisy [2], blurry [3] or corrupt image [4].

Blur has been one of the general artifacts of the given digital images, the main reason behind blurriness is that the camera fails to locate in focus or the camera has not been held steadily, the other reason also could be the moving of subjects over the exposure periods. These phenomena occurs as the image sensor gathers the lights from the various regions.

Hence one end up capturing the blurry image with adequate detail and unclear edge, these results in degrading of image quality. Several blind algorithm were presented for removing these artifacts. The process of recovering from the blurred image has been quite challenging specially when there is no explicit information is available for the blur function. In the computational imaging literature, motion deblurring is an important topic because camera shakes are common during the photography procedure.

In recent years, this topic has attracted growing attention thanks to the popularity of smartphone cameras [5]. On such platforms, the motion deblurring algorithm plays an especially crucial role because effective hardware solutions such as professional camera stabilizers are difficult to deploy due to space restrictions. In last few years, we have observed the significant growth in Image De-blurring, moreover in this section we have discussed the several existing method that has helped in restoring the image.

In [6]author have encoded the image blocks by using over-complete sparse coefficient for encoding the image blocks, similarly [7] combined the SP(Sparse prior) of the given natural image along with the improvised version of absolute group of dictionary, this efficiently exclude the detrimental structure. [8] Used the normalization for representing the frameless sparsity through a multiscale approach, which proceeds from the course to the fine resolution. Moreover, [9] implied the LR (Low-Rank) model along with the WNN (Weighted Nuclear Norm) and minimization process is used for fitting the LR-matrix. Moreover, this particular method aims for fining the texture details while maintaining the DS(Dominant Structure) of the given blurred image.

Later, [10] introduced a novel methodology which uses the information through the dark channel , however the dark channel fails miserably in order to hold the image where the bright pixels is one of the important thing to be considered. Moreover, the method like [11] used the Deep-CNN as well the model of total variation in image distortion for the application of Image deblurring, however the efficiency as well as the convergence of the above method are not well balanced. Some of the researcher have given attention for the eminent feature learning and through this few of them have proposed a few effective such as [12] [13].

Moreover, in the above technique there has been several drawbacks, which are mentioned below.
1.   Efficiency and convergence properties of this algorithm has not been well balanced.
2.   All these algorithms are impractical for the Computer vision applications due to change in parameters.
3.   Some of the optimization problem described above are costly

However, convergence and efficiency properties of the mentioned algorithms have not been well balanced. Additionally, some researchers have paid more attention to salient-edge extraction and selection to propose a number of effective deburring methods [15]. Most deburring methods focus on special scenarios, such as low illumination, text and faces.

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These domain-specific methods require complex operations and lack universality.

This particular research work is organized in the any IEEE standard format, Here first section starts with the introduction about the image restoration later part of the section discuss the various existing technique for restoring the image, followed by this second section discuss the motivation for de-blurring and contribution of this research work. Third section gives the details about proposed methodology along with the flow diagram and mathematical notation. Fourth section evaluates the CCM based model by considering the Levin dataset. In the next section, we conclude our research work.

Motivation and Contribution

Image Restoration aims to restore and enhance the image computationally by reversing the adverse effect of the degradation of the image such as blur. Moreover, De-blurring has been one of the key area of restoring the image and it has various application that ranges from the pattern recognition, computer vision to morphologic qualification to the machine learning. Considering the application of the De-blurring it becomes eminent to develop a method for restoring the image through de-blurring, hence in this research work we propose a novel approach for image deburring based on the constrained conditional model. Contribution of this research is summarized through the below points.

- We develop a methodology based on constrained Conditional model, which helps in restoring the blurred image in efficient way.
- Conditional model approach is used for restoring the image that has been caused due to the object movement, camera shakiness and other physical movement.
- Improve the reconstruction quality.
- Our approach is robust in case of low-level problems and possesses good PSNR and SSIM value.
- When compared with the various state-of –art technique CCM outperforms the other model.

II. PROPOSED METHODOLOGY
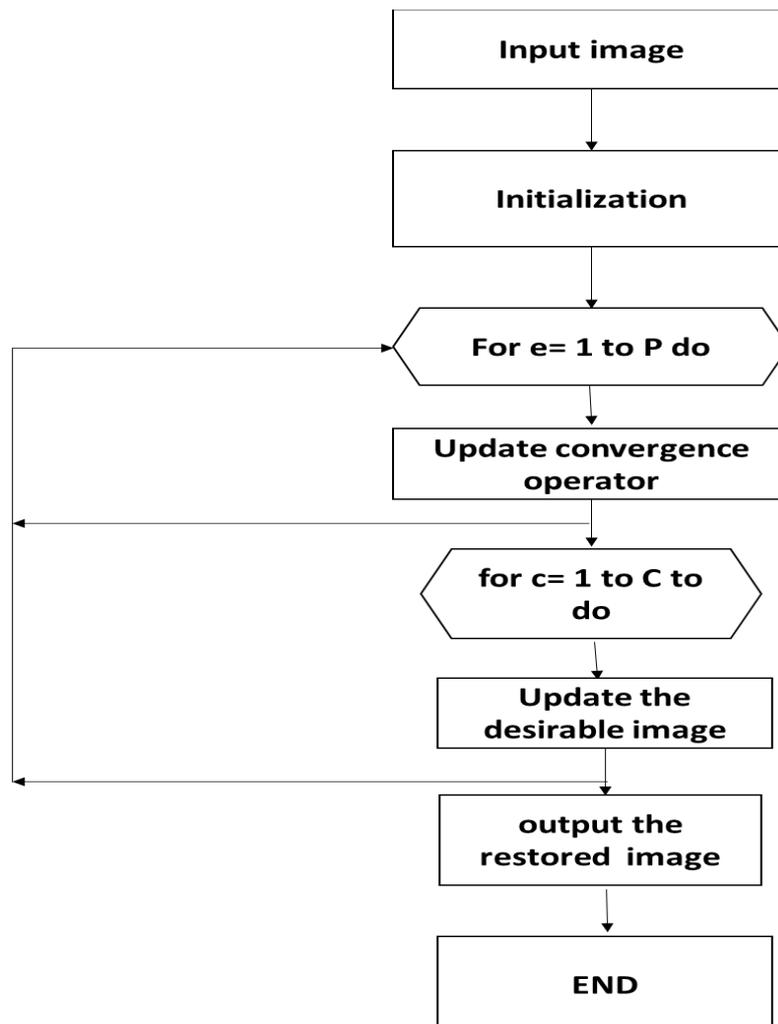
Figure 1 proposed flow work of deblurring based on CCM

Figure 1 represents the proposed flow of our work. Here at first we take input as the deblur image and then we initialize the desired image, desired image is the expected image, later we achieve the approximation through the convergence operator. Approximation is achieved by updating the convergence operator similarly each stage are updated along with the desired image, hence through the CCM model and approximation we achieve the desired image i.e. De-Blur image.

In order to generalize the filter a framework is considered that can capture the natural scene statistics and learn the expressive and the generic prior model for the low-level vision problems. Moreover, with this framework we find the way to learn the MRF (Markov random Field).

Hence the overall framework can be described through the below equation. Equation 1 represents the objective function,

$$\frac{\lambda}{2}\|I_1 - MI_2\|_2^2 + \sum_{n=1}^{R}\omega_n(B_n I_2) \qquad (1)$$

Here I_1 and I_2 represents the image observed and desired image respectively. M Indicates the convolution operator, which senses and B_n indicates the 2D conv along with the given filter b_n. ω_n Is used as the penalty function, which is used for solving the issue of constrained optimization. λ Indicates the positive scalar, which helps in balancing the regularization and data fidelity and λ depends on the parameter and the task assigned.

Moreover several researcher have used to achieve the restoring the image by considering the equation 1 as the objective , they trained this model for mapping the model , some of them achieved the tradeoff among the time and quality , however the main issue here comes through this objective is that it needs the separate training for each individual task. This is one of the major drawback and hence the previous method has failed.

A. Dividing problem into sub-problem and approximation.

Moreover, the equation 1 is considered as the objective function and cannot be optimized directly when the penalty function ω_n is non-linear hence we use the convergence operator this helps in parting the problem into various sub-problem. We compute the nonlinear estimator the one that is derived from the non-convex regularization. Furthermore, this is considered as the approximation problem hence this needs to be relaxed. Thus, we relax the function through using the convergence operator and introduce the new objective, which is described through the equation 2. Convergence operator needs only few iterations to achieve the result and objective is summarized in the given below equation.

$$\frac{\lambda}{2}\|I_1 - MI_2\|_2^2 + \frac{\varphi}{2}\|(CO) - M\|_2^2 \sum_{n=1}^{R}\omega_n \qquad (2)$$

M is the convolution operator for the deburring, φ is positive scalar and moreover λ is dependent on both i.e. parameter as well as task in order to generate the absolute accuracy. CO is variable that is used to form the equality in inequality constraint. Furthermore, Equation 2 is optimized

iteratively through CO variable solving the desired image I_2. Meanwhile Equation 3 and Equation presents the iterative optimization where

B. Approximation through Convergence operator

$$CO_e = {}^{argmin}_{CO}\left(\frac{\varphi^e}{2}\|Co - M^{e-1}\|_2^2 + \sum_{n=1}^{R}\omega_n(B_n CO)\right) \qquad (3)$$

$$I_{2e} = {}^{argmin}_{I_2}(\lambda\|I_1 - MI_2\|_2^2 + \varphi^e\|CO_e - I_2\|_2^2) \qquad (4)$$

Here φ^e keeps on increasing with increase in iteration, this leads CO to be the ideal approximation of I_{2e}.

A new partition technique is applied for above technique and this divides the problem into its two category i.e. convergence operator and Distributed convergence operator respectively. Here adaptive approach of CCM trains the model. Further, it is observed that the above problem is NCO (Non-Convex Optimization) problem and non-deterministic algorithm.

CCM (Constrained Conditional Model) approach

Equation 4 is dependent since the matrix M as well as fidelity weight λ are the problem specific and the convergence operators are totally independent of the restoration task. CCM (Constrained Conditional model) approach are transferable and it can be placed instead of convergence operator, which is embedded in optimization.

Moreover, convergence operator i.e. equation 3 is interpreted as deburr on the given image. Hence, here we apply the constrained conditional model and we get the equation.

$$CO_e := COP_\Theta(M^{e-1}, \varphi_e) \qquad (5)$$

COP is the Convergence operator and Θ indicates the amount of filter used. Later COP_Θ is processed for learning. Moreover, for iteration in equation 3 and equation 4 we use the same model parameter for each iteration.

C. Distributable Convergence operator:

In here we use the MND (multiple stage diffusion) process and this is based on the non- linearity.

$$CO_e{}^c = CO_{e-1}{}^c - \sum_{n=1}^{R}B_n{}^{c^P}\psi_n^c(CO_e{}^c CO_e{}^{c-1}) \qquad (6)$$

Such that

$$CO_e{}^o = M \qquad (7)$$
$$c = 1,2,\dots C$$

c is the stage index and $B_n{}^c$ is the filter, ψ_n^c is the trainable parameter in the initial stage and later stage as well.

At last, for the training task we consider the de-blurring at training where M is matrix, which represents the 2D conv with random blur kernel drawn.

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III.   RESULT AND ANALYSIS

In order to evaluate the performance of proposed methodology, we have used the MATLAB as a platform with i7 processor and 8 GB RAM. Moreover, for evaluation we have used the Levin [14] Dataset, it is the gray scale image.

Table 1 shows the evaluation of Levin dataset with eight different Blur kernel i.e. Figure a to h presents the BK1 to BK8.

Table 1 different image retrieved through the various kernel

a)

b)

c)

d)

e)

f)

g)

h)
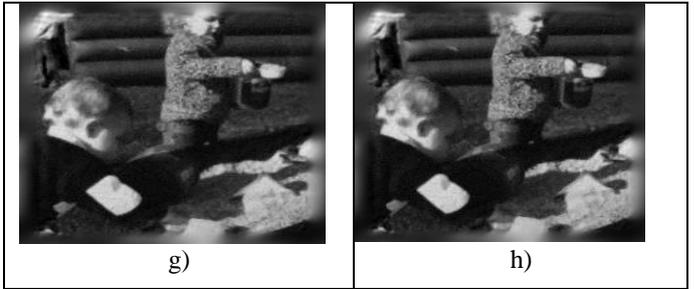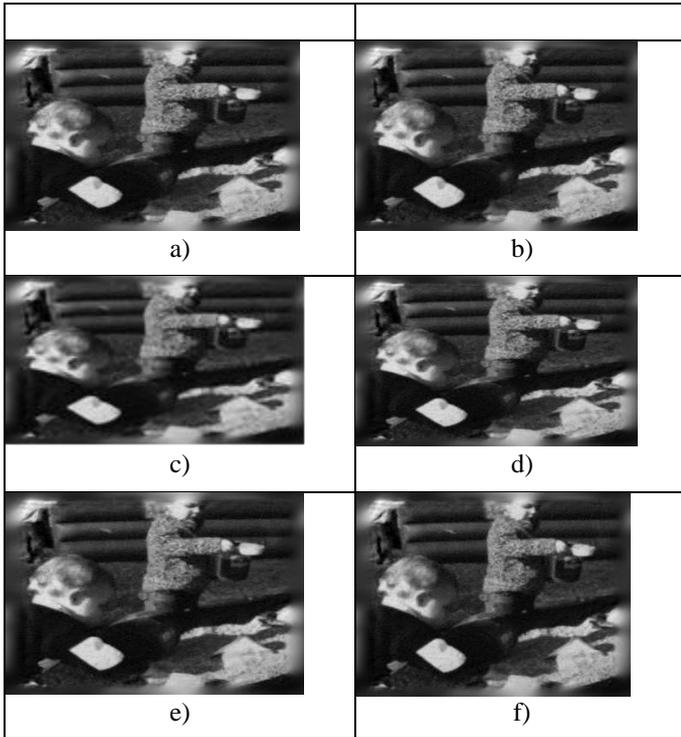
A.   Performance metric

For further evaluation of the proposed methodology we have consider the two major metrics i.e. PSNR and SSIM [14].

In order to evaluate our algorithm, the comparative analysis has been with the state-of-art technique, comparison is done based on the PSNR or Peak to signal NR (Noise Ratio) and SS (Structural similarity) Index.

B.   PSNR

PSNR is the parameter, which is used for comparing the quality of image compression. When standard algorithm and state of art technique is compared. We observe that for first kernel existing methodology gets 21.952 where as our methodology achieves 32.08, similarly second Blur kernel achieves the PSNR value of 18.735 and 32.19 for the CCM based methodology. Moreover, it is observed that from the entire eight kernel achieves the PSNR value of 15 to 20 for all state- of- art technique whereas our methodology achieves the PSNR value of 32.

Table 2 Comparison of Mean PSNR with various state-of-art technique

Kernel	[15]	[16]	[17]	[18]	[19]	PS
BK1	19.619	20.642	19.704	20.889	21.952	32.08941
BK2	16.962	18.1369	17.845	17.643	18.735	32.19083
BK3	18.213	19.611	19.006	19.374	20.178	32.19083
BK4	15.861	16.316	17.575	17.901	18.886	32.0874
BK5	18.393	18.257	17.983	18.021	19.475	32.0856
BK6	16.703	18.213	16.548	16.494	17.562	32.14796
BK7	19.157	17.955	18.414	17.951	19.827	32.15783
BK8	16.069	18.025	17.707	17.739	20.065	32.20403

C.   SSIM

In later part of this section, the comparison is also done based on the SSIM (Structural Similarity) Index. SSIM is the metric, which quantifies the degradation in the image, this degradation might occurred due to the various factor, here the first blur kernel achieve the 0.76 whereas proposed model achieves the 0.809 , second blur kernel observes the value of 0.71 and CCM based model observes the value of 0.81. Moreover, it is observed that on an average all these state-of-art technique observes the value of 0.7 including the existing methodology whereas proposed methodology achieves the value of nearly 0.80 to 0.81, which is comparatively higher than these other methodology.

Higher value of SSIM indicates the better efficiency of model.

Table 3 Comparison of Mean SSIM of various state-of-art technique

Kernel	[15]	[16]	[17]	[18]	[19]	PS
BK1	0.6899	0.7294	0.6996	0.7075	0.7602	0.809671
BK2	0.5041	0.6717	0.6626	0.6352	0.7140	0.810127
BK3	0.6724	0.7796	0.7354	0.7607	0.8086	0.810127
BK4	0.4368	0.4446	0.5505	0.5515	0.6414	0.809738
BK5	0.6257	0.6127	0.6058	0.5964	0.6766	0.809518
BK6	0.4833	0.5807	0.1508	0.4922	0.5894	0.810013
BK7	0.6254	0.5653	0.5922	0.5611	0.6333	0.811058
BK8	0.3949	0.5935	0.5753	0.5393	0.6871	0.810954

IV. CONCLUSION

This research work aims at restoring the image by proposing a novel approach based on the Constraint conditional model, this approach develops the reconstruction model of the image caused due to the blur artifacts. Moreover, CCM based methodology performs better than the other state-of-art technique by considering the 8-blur kernel and in each kernel CCM based model excels in terms of PSNR and SSIM. Moreover the PSNR value observed in case of CCM based model is on an average 32 and similarly the mean SSIM observed is 0.81 , hence the value is comparatively higher than the other state-of-art technique, this shows that CCM based model for de-blur outperforms the other model.

Moreover, in here, we have considered the gray scale image and in future we would be performing on the different dataset and the colored image for further evaluation, however considering the performance of the model this can be further helpful towards developing de-blurring technique.

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