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Adaptive Deblurring by Estimation of Motion Blur Kernels

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Abstract— One of the challenges in the field of photography is the motion blur. Motion blur is the smudging of images caused by the relative motion between the camera and the pictured object during the exposure time. Blur kernel is the fundamental cause for blurring. Thus, in order to restore the original image through deconvolution, we need to estimate the blur kernel. In this paper, the blur kernels are estimated by using a piecewise linear model. Then, estimated kernel is regularized by adjusting the spacing and curvature of the control points. In addition to this, the control parameters of the energy function is also optimized in order to achieve better edge enhancement. The estimated kernel is then optimized by using Gauss- Newton method. In order to improve the PSNR of the deblurred image, wavelet multiframe denoising is used. In addition to this, the quality of image is enhanced by using a colour image enhancement technique. The experimental result shows that, kernel estimation along with wavelet multiframe denoising and Colour image enhancement technique can improve the PSNR values as well as the quality of the resultant deblurred image. In addition to this, the proposed algorithm can accurately estimate the unknown kernel masked in the blurred image, without any prior knowledge.

Index Terms—Motion blur, Piecewise-linear curve, Kernel estimation, Deblurring, Wavelet multiframe denoising, PSF, Blind deconvolution, Image enhancement.

I. INTRODUCTION

ONE of the salient source of degradation of images in digital imaging technology are the motion blur. Blurring artifacts are due to the relative motion between the camera and the pictured object, while capturing the images with longer exposure time. Technically, if the motion blur is shift invariant, blurred image can be modelled as the convolution of original latent image with blur kernels, with the addition of some noise.

$$B = S * K + G \quad (1)$$

where, B is the blurred image, S is the ideal image, G is the noise, and * represents the convolution operation.

To avoid blur, we need to capture the images with shorter exposure time or try to remove the blur offline. Removing the motion blur artifacts from the image is often referred to as motion deblurring, which is a very challenging task.

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Since, blurring is a convolution operation, deconvolution algorithms are used to restore the images attenuated by the blurring artifacts. If the deconvolution process is performed with any prior knowledge about the masked kernel or original latent image, it is referred to as non-blind deconvolution, otherwise it is referred as blind deconvolution process.

The authors in [1], have demonstrated a fast motion deblurring technique. The algorithm accelerates the blur kernel and latent image estimation, using an iterative deblurring technique, which is the combination of a prediction step and a non-blind deconvolution algorithm. In fast two phase image deblurring under impulsive noise [2], a two phase approach is used to restore the images corrupted by motion blur and impulse noise. The first phase identified the pixels corrupted by impulsive noise. Then, in the second phase, a variational method is used to deblur and denoise the images simultaneously. But, there is no good detector available for random valued noise, when the noise ratio is high.

Motion blur identification from image gradients [3], uses a hybrid Fourier-radon transform technique to estimate the blur kernel parameters. But, the uniform velocity motion blurring due to camera shakes cannot be modeled using this method.

In the approaches based on the piecewise linear models, such as Piecewise linear motion blur identification using morphological filtering in frequency domain [4], and Identification of piecewise linear uniform motion blur [5], motion components are estimated independently based on the spectral analysis of an image. Then, these components are assembled together to form a complete kernel.

In [6], the translation of the sensor plane during exposure time T can be expressed as an arbitrary parametric curve in a 2-dimensional continuous domain. It is then further approximated by using a piecewise-linear curve by connecting the control points.

This paper presents an adaptive deblurring technique by estimating the blur kernels using a piecewise linear model and regularizing the estimated kernel by adjusting its spacing and curvature using simulated annealing algorithm. As a final processing, the kernel is optimized by using a Gauss- Newton method. The estimated kernel is deconvolved with the given blurred image, in order to restore the ideal image. Then, wavelet multiframe denoising is used to improve the PSNR of the deblurred image. Finally, an image enhancement technique is used to improve the quality of the resultant image. The paper is organized as follows. The brief description of the proposed algorithm is given in section II. The Piecewise linear representation of the blur kernel is briefly explained in Section III.

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Section IV, explains the regularization using simulated annealing algorithm. Section V, gives the details regarding the optimization of estimated kernel. Final deconvolution is given in section VI. Section VII gives denoising and quality enhancement of deblurred image. Section VIII gives results and discussions. Finally, conclusions are given in Section IX.

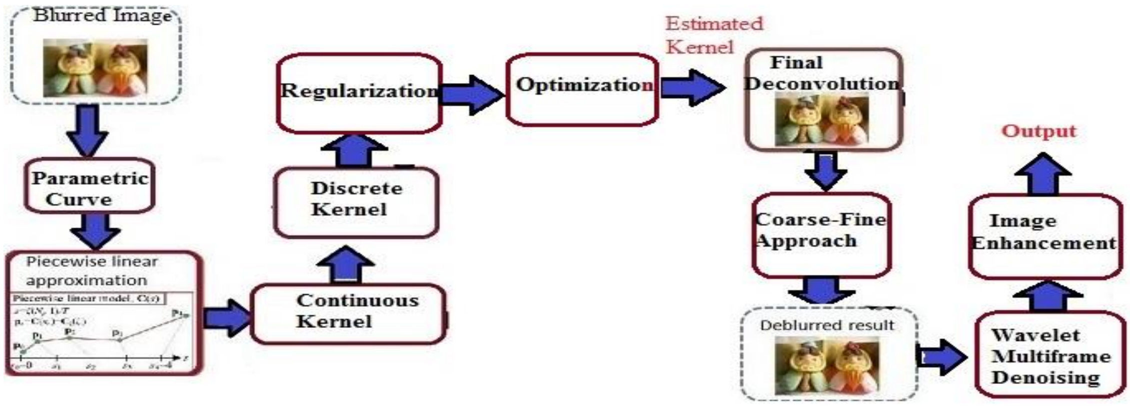

Figure 1: Overview of the deblurring process

II. PROPOSED SYSTEM

This paper proposes an effective approach for estimating the blur kernels using piecewise linear model. Initially, a blurred image is given as the input. The translation of sensor plane during the exposure period, T is represented as an arbitrary parametric curve. This curve is then approximated by using a piecewise linear model by fixing some control points. Piecewise linear curve is then projected to a continuous kernel using a projection operator, $\mathcal{P}$. Continuous kernel is discretized using a discretization operator, $\mathfrak{D}$ to generate a discrete kernel. The discrete kernel is then regularized by adjusting the spacing and curvature as well as control parameters. The estimated kernel is then updated by alternating the optimization between the kernel and latent image estimation. Finally, the updated kernel is deconvolved with the input blurred image in order to restore the ideal latent image. To improve the PSNR and quality of the estimated image, Wavelet Multiframe denoising along with colour image enhancement technique is used.

Fig. 1 shows the block diagram of overall adaptive deblurring technique by the estimation of blur kernels and the denoising and enhancement of the resultant deblurred images.

III. PIECEWISE LINEAR REPRESENTATION OF BLUR KERNEL

The intensity transformation during the exposure time, T can be plotted in 2 dimensional continuous domain as an arbitrary parametric curve, $C_\theta(\theta)$, which is given in figure 2. This arbitrary curve is then approximated by using a piecewise linear model by fixing N_q number of control points, $q_i = [q_i^{(x)}, q_i^{(y)}]$, $i = 0, 1\ldots N_q - 1$.

The piecewise linear curve C (j, K), is the concatenation of (N_q– 1) line segments.

$$C(j; K) = I(j - j_i; q_i - q_{i+1}) \qquad (2)$$

Each line segment in the piecewise linear curve is projected
by integrating it with a Dirac impulse function, δ (ρ-I).

$$C_i(\rho, K) = \mathcal{P}\{I(\chi; q_i - q_{i+1})\}$$

$$= \int \delta(\rho - I(\chi; q_i - q_{i+1}))\, d\rho \qquad (3)$$

By adding each of C_i (ρ, K) and normalizing with a normalizing constant, [$1/N_q$-1], a continuous kernel, C (ρ, K) can be obtained.

$$C(\rho, K) = [1/N_q - 1] \sum C_i(\rho, K) \qquad (4)$$

To obtain a discrete kernel, the continuous kernel is discretized using a discretization operator, which is a triangular kernel, obtained by the convolution of two triangular functions in two different domains.

The triangular kernel is given by,

$$\blacktriangle(\rho, \theta) = \mathrm{tri}(\rho) * \mathrm{tri}(\theta) \qquad (5)$$

Thus, the discrete kernel is given by,

$$C(x, K) = \mathfrak{D}\{C(\rho, K)\}$$

$$= \int \delta(\rho - x).\, (\blacktriangle(\rho, \theta) * C(\rho, K))\, d\rho \qquad (6)$$

Finally,

$$C(x; K) = \mathfrak{D}[\mathcal{P}[C(j; K)]] \qquad (7)$$

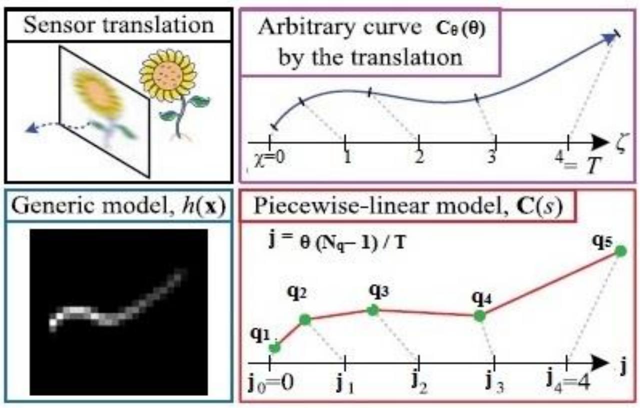

Figure 2: Focal plane translation due to camera shakes and blurs kernel representation for N_q = 5 [6].

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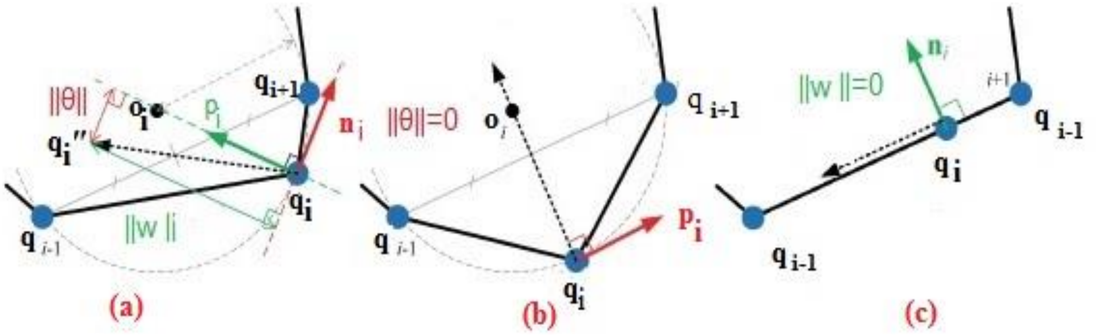

Figure 3: Regularization of piecewise linear model by readjusting the control points [6]. (a) Configuration of control points. (b) Control points are equidistant from one another. (c) Control points lie in the same line segment.

IV. REGULARIZATION USING SIMULATED ANNEALING ALGORITHM

The discrete kernel formed by piecewise linear approximation is regularized by adjusting the spacing and curvature of the control points, to bring off a best estimate of the kernel. The regularization scheme can be represented as,

$$J_R(K) = \alpha\, J_{sk}(K) + \beta\, J_{Ck}(K) \qquad (8)$$

where, J_{Sk} and J_{Ck} represents spacing and curvature regularization energies, respectively and α and β are the parameters used to maintain the relative importance of both the energy functions. The energy terms are used to reflect the divergences of predicted kernel from the desired configuration [6].

Consider two auxiliary vectors θ and ω, in order to readjust the control points of the discrete kernel, such that, each control points will be equidistant from their neighboring points, when ‖θ‖= 0 and all the control points should lie on the same line segment, when ‖ω‖= 0.

$$\theta = [\ldots, q_i^{''(x)}\, n_i^{(x)},\ c_i^{''(y)}\, n_i^{(y)} \ldots];$$
$$\omega = [\ldots, q_i^{''(x)}\, p_i^{(x)},\ q_i^{''(y)}\, p_i^{(y)} \ldots]; \qquad (9)$$

where, pi, n_i and q_i”, are the unit normal vector, unit tangential vector and second derivative of C(x; K).

From the Figure 3,

$$q_i^{''} = \frac{q_{i-1} - 2q_i + q_{i+1}}{\{1/(N_c-1)\}^2}\ ; \quad p_i = \frac{(o_i - q_i)}{\| o_i - q_i \|}$$
$$n_i = [-p_i^{(y)}, p_i^{(x)}]^T \ ; \qquad (10)$$

where, n_i is obtained by perpendicularly rotating p_i. ‖θ‖ and ‖ω‖ are equivalent to the norms of inner products,

$$\|\theta\| = [q_i^{''}.\, n_i];\ \|\omega\| = [q_i^{''}.\, p_i]; \qquad (11)$$

Since, J_S (K) and J_C (K) can be expressed as the squared sum of ‖θ‖ and ‖ω‖, spacing and curvature regularization can be achieved, when ‖θ‖ and ‖ω‖ become 0.

$$J_S(K) = ½\sum \|\theta\|^2; \quad J_C(K) = ½\sum \|\omega\|^2; \qquad (12)$$

The control parameters α and β are also optimized using simulated annealing algorithm (SA), along with spacing and curvature regularization,

The main advantage of using SA algorithm is that, it allows to escape from the trap of local optima, and to reach the global optima. Optimization using simulated annealing algorithm is given in Algorithm 1.

Algorithm 2: Optimization using SA algorithm

At a fixed temperature, T=1,
Cost function = Finding the mean value,
Set an upper bound and lower bound,
Termination condition, $\sigma = 10^{-3}$.
1) Choose a random value for α and β, and calculate its cost function.
2) Choose another value for α and β randomly and calculate its cost function also.
3) Compare them:
- If $c_{new} < c_{old}$: move to the new solution
- If $c_{new} > c_{old}$: accepted new solution with probability,

$$\mathbf{exp\ ((c_{old} - c_{new})/T).}$$

4) The acceptance probability is compared with a random number between 0 and 1.
5) If the acceptance probability is larger than the random number, switch.
6) Decrement temperature, T= T*ε, where ε = 0.97
7) Repeat steps 3-5 above until T< σ is reached.

Thus, the regularization energy of the kernel, J_R can be minimized by the simultaneous minimization of spacing and curvature regularization energies as well as the control parameters. Thus, it provides an elongated and equally-spaced configuration of control points to form curvy shape for kernel instead of spread out one [6].

V. OPTIMIZATION OF THE KERNEL

The kernel obtained by the piecewise linear approximation is optimized using the Gauss Newton method. The update equation of K_T, at the T_{th} step is given by,

$$K_{T+1} = K_T - (H_K(K_T) + \mu S)^{-1} \Delta J_K(K_T) \qquad (8)$$

where, δJ_K and H_K represents the gradient and the Hessian matrix of the kernel respectively. The parameter μ, determines the rate of convergence.

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Larger the μ value, slower but stable convergence can be achieved.

$\Delta J_K = \Delta J_D + \Delta J_R$
$H_K = H_D + H_R$ (9)

The J_D is the squared sum of data fitting term d(x, K),

$\Delta J_D = \sum d(x, K_T)\, \Delta\, d(x, K_T)$
$H_D = \sum d(x, K_T)\, \Delta\, d(x, K_T)^T$ (10)

where, d(x, K) = S(x) * K(x) – B(x), data fitting term. ΔJ_R and H_R are obtained by fixing Q and N temporarily.

$$\Delta J_R (K_T) = T^T (\alpha\, Q_T + \beta\, N_T)\, T\, K_T$$
$$H_R (K_T) = T^T (\alpha\, Q_T + \beta\, N_T)\, T \quad (11)$$

Thus, the best estimate is obtained by optimizing the kernel through different iterations.

VI. Deconvolution

Once the kernel, K is obtained, it is deconvolved with the input blurred image, B in order to restore the original latent image, I. Then, best estimate of the kernel and latent image is obtained by alternating the optimization between kernel estimation and deconvolution, as summarized in algorithm 2 [6].

Algorithm 2: Deblurring process

S(x): Latent Image
K(x): Blur Kernel
1) K' = K_{init}, S' = S_{init}
2) For iter= 1 to N_{iter} do
3) Kernel Estimation, K (x) = argmin (J_K (K))
4) Deconvolution, S(x) = K (x) * S(x) - B(x)
5) S' =predict (S (x))
6) End for
7) Return S' and K'

A. Coarse to Fine Approach

A coarse- fine approach is employed in order to refine the estimated kernel as well as the latent image, after optimization. The efficiency of kernel is increased by increasing the number of levels in coarse-fine approach. The kernel and the latent image estimated during the current iteration, are used as the input for the next finer level. By exhaustively searching for the line segment that minimizes the energy of the kernel, J_D (S_{init}, K), it can be updated. The control points play a major role in controlling the balance between the flexibility and simplification of estimated kernel. Assigning large number of control points result in unambiguous estimation. Thus, a few number of control points were chosen for efficient estimation process. In this work, N_q is set to be 5. The complete process of coarse- fine approach is summarized in algorithm 3 [6].

Algorithm 3: Coarse- fine Approach [6]

N= no. of levels, i = N denotes the coarsest.
Set N_q = 5
For i = N to 1 do
If i = N, then
K_{init} (N) = *ExhaustiveSearch* (S_{init} (N), B (N))
Else
N_q = $2N_q$
{S_{init}, K_{init} (i)} = *Upsample* {S' (i+1), K' (i+1)
End if
{S' (i), K' (i)} = *SingleLevelDeblur* {S_{init} (i), K_{init} (i), B (i)}
End for
Return S' (i), K' (i)

VII. Denoising And Image Enhancement

A) Wavelet Multiframe Denoising

Instead of averaging the multiple image frames or denoising the estimated image, the algorithm performs wavelet decomposition of each frame for noise as well as structure estimation. In addition to this, detailed coefficient of the wavelet transform are weighted, averaged and reconstructed.

The main steps of wavelet multiframe denoising algorithm are summarized as follows [8]:

1. Using the logarithmic transformation, each image S_i, S = 1, 2… N, are scaled.
2. The scaled image undergo wavelet decomposition.
3. Weights are estimated from wavelet coefficients and applied to the detailed coefficients [8].
4. Averaging the resultant image in wavelet domain.
5. Finally, wavelet reconstruction will yield the reconstructed image, R.

Fig. 4 shows the flow diagram of the wavelet multiframe denoising technique.

The processing steps will be explained in detail below.

Logarithmic transformation: In the logarithmic scale space, a near additive noise model is assumed. The input to the denoising model is a noise corrupted ideal image, S_i.

$$S_i = I + N_i \quad (12)$$

Moreover, each image is having the same standard deviation at the position y for the noise, σ_i (y).

i.e,

$$\sigma_i (y) = \sigma_j (y) \quad (13)$$

Wavelet Decomposition: Each frames of the image are decomposed into maximum number of levels, L_{max} using wavelet transformation. The wavelet decomposition is produce two coefficients, i.e., approximation and detail coefficients. For comparison, two different wavelet transforms, such as discrete stationary wavelet transform with Haar wavelet and dual tree complex weight transformation is utilized. Approximation coefficients in each of the levels, from both of the wavelet decomposition operation are collected.

Coefficient Weighting, averaging and wavelet reconstruction: For denoising, detailed coefficient at the position y is weighted using a weight μ. After coefficient weighting, detailed and approximation coefficients are averaged. Finally, the inverse wavelet transform of the averaged coefficients produce denoised image.

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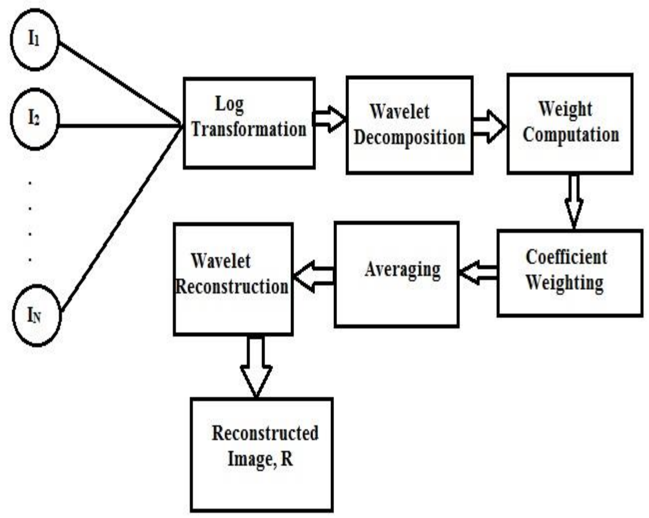

Figure 4: Flow diagram of Wavelet Multiframe Denoising [8]

B) Colour Image Enhancement Technique

The image enhancement technique is used to highlight the useful information and to obtain the fine details present in the image. There are different types of enhancement techniques. In this paper, two techniques such as, contrast stretching and histogram equalization is used to compare their performance.

1. **Contrast Stretching [9]:** Dynamic range of the image is stretched using this technique. Dynamic range is referred to as the range between the maximum and minimum intensity range in the image. Contrast stretching is given by,

$$S'(x, y) = d / (S_{max} - S_{min}) \times (S(x, y) - S_{min}) + S_0 \quad (14)$$

where, S'(x, y) is the updated dynamic range, d is the value of new dynamic range, S(x, y) is the input image and S_{max} and S_{min} are the maximum and minimum intensity values. S_0 is the offset point of new dynamic range for S' (x, y) [9]. The resultant image will give good visual resolution of the original scene.

2. **Histogram Equalization [9]:** In this method, the contrast is adjusted using the image histogram. Histogram of the scene is remapped to the histogram that has a near-uniform pdf. Intensity distribution is redistributed in this method. The peaks and valleys in the histogram of the image is shifted after the equalization procedure. This method improves the contrast as well as provides uniform histogram.

VIII. EXPERIMENTAL RESULTS

To evaluate the efficiency of the proposed model in dealing with various types of blurs, a set of blurred images were created manually. Let, the original latent image be L and the blurred image be K, the blurred B is the result of the convolution of latent image with the blur kernel and the addition of some noise. i.e., B = L* K + N

A. Experiments with blurred images

The experiment is implemented in MATAB. Initially, a blurred image of size 128 X 128 was chosen as the input. Then, sensor translation is represented as arbitrary parametric curve. This curve is then approximated by using a piecewise linear model by fixing some control points. Here, we set N_r = 10. Piecewise linear curve is then projected to a continuous kernel and then discretized to a discrete kernel. The discrete kernel is then regularized by adjusting the spacing and curvature. The control parameters α and β values were chosen iteratively using simulated annealing algorithm. The estimated kernel is then updated by alternating the optimization between the kernel and latent image estimation. Finally, the updated kernel is deconvolved with the input blurred image in order to restore the ideal latent image.

Fig 5. shows the input blurred image of size 128 X 128 and its transition curve. Then transition curve is piecewise linear approximated by fixing 5 control points. Then, regularization of the control points are also shown in the figure. The estimated kernel after regularization is optimized using Gauss Newton method and finally, optimized kernel is deconvolved with the given blurred image in order to restore the original latent image.

Fig. 6 shows the set of three blurred images of size 128 X 128 and the estimated kernel using the proposed piecewise linear model. From the figure itself, it is clear that the proposed algorithm is efficient in identifying the kernels masked in the blurred images.

Fig.7 shows the reconstructed image formed by 1) the piecewise linear model by Sungchan and Gyeonghwan [6], and 2) the proposed model.

B. PSNR Estimation

The blur kernel models to be evaluated are: 1) Two-phase kernel estimation for robust motion deblurring [10], 2) the piecewise linear model by Sungchan and Gyeonghwan [6], and 3) the proposed model.

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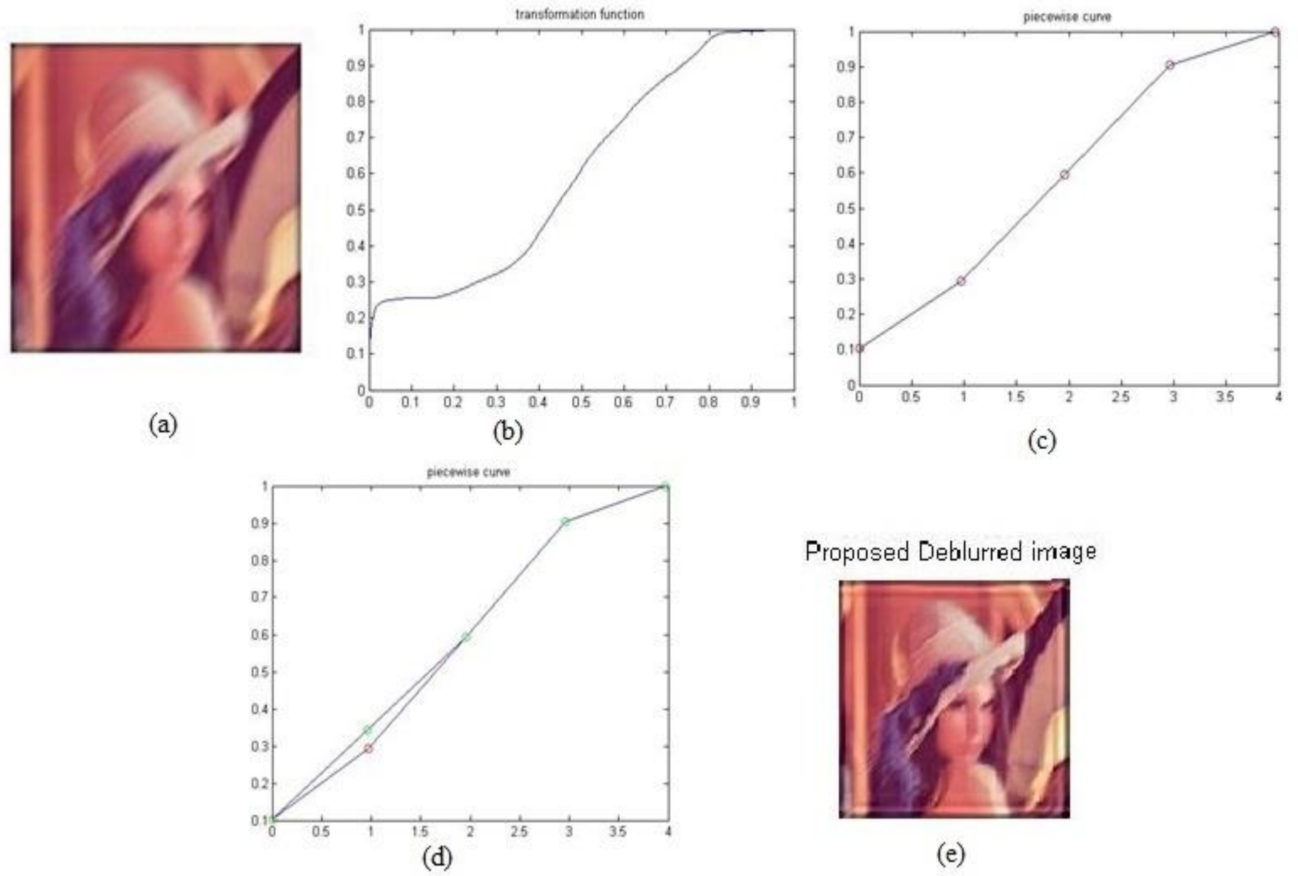

Figure 5: (a) Dataset Image S_1 of size 128 x 128, (b) Sensor plane translation of dataset image, S_1 (c) Piecewise linear approximation of parametric curve, (d) Regularization of control points, (e) Deblurred image.

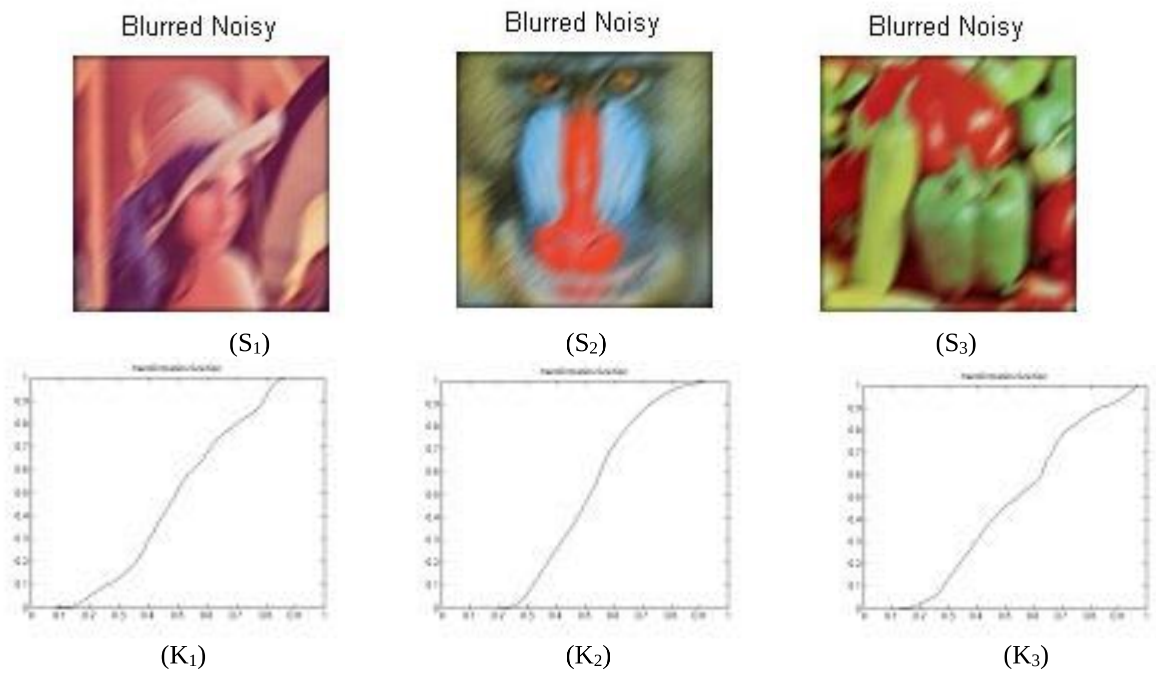

Figure. 6. Dataset images for the experiments. Motion blurred images,S_1-S_3 are given from left to right and their corresponding estimated kernels K_1-K_3 are given below. The images are of size 128 X 128. Estimated kernels are of size 150

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(a)

(b)

Figure 7: (a) Dataset Image S_1 of size 128 x 128 (a) the result of piecewise linear model (PSNR = +40.33517 dB) (d) the result of proposed model (PSNR = + 58.40711 dB).

PSNR is used as a qualitative tool for analysis. PSNR values of the Two-phase kernel estimation for robust motion deblurring [10], Piecewise linear model and proposed model for the three dataset images were computed and the values were recorded in Table1.

TABLE I: PSNR VALUES OF Xu AND JIA [10], PIECEWISE LINEAR MODEL [6], AND PROPOSED ALGORITHM.

Methods	S_1	S_2	S_3
Two-phase kernel estimation	+32.885	+29.225	+35.776
Piecewise Linear [6]	+43.69856	+46.21779	+44.17716
Blind Deconvolution+ Denoising	+ 58.40711	+ 51.43268	+ 49.32256

The different parameters estimated using Piecewise linear model [6] and the proposed model for three dataset images were given in Table 2.

The performance analysis of contrast stretching and histogram equalization technique for image enhancement were summarized in Table 3.

From the table 3, it is concluded that, the histogram equalization technique will provide better flatness value and also preserve the image brightness effectively.

TABLE II: PARAMETERS ESTIMATED USING PIECEWISE LINEAR MODEL, AND PROPOSED ALGORITHM.

Method	B.I	PSNR	MSE	RMSE	SNR	MAE
Piecewise Linear [6]	S_1	+43.698	381.4	22.19	-2.8	15.5
	S_2	+46.217	930.6	32.58	-6.4	19.2
	S_3	+44.177	720.9	34.018	-6.5	21.2
Proposed Method	S_1	+59.00	0.982	0.317	-0.4	0.017
	S_2	+47.40	1.392	3.039	-0.9	0.207
	S_3	+45.91	1.630	2.30	-0.2	0.571

TABLE III: PERFORMANCE ANAYSIS OF DIFFERENT IMAGE ENHANCEMENT TECHNIQUE

Method	Flatness Value	Contrast per pixel	Average Mean Brightness Error
Contrast Stretching	1226.1185	4.2699	22.1924
Histogram Equalization	115.9456	5.1296	16.6760

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IX. CONCLUSIONS

Motion blur removal is the one of the challenging task in the field of image processing. The proposed deblurring algorithm uses piecewise linear approximation along with the combined process of denoising and image quality enhancement technique can effectively identify the blur kernels present in the blurred images. In this work, control parameters of the energy function are regularized using simulated annealing algorithm. After regularization, the kernel is optimized to obtain a good estimate. This kernel is deconvolved with blurred image to recover original image from the blurry version. The proposed model is very efficient in dealing with various types of blur as well as noise. Regularization with simulated annealing algorithm leads to edge enhancement. This method can also improve the PSNR values and quality of estimated image than other conventional deblurring techniques.

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