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Comparison of Different Noises for Scene Text De-Blurring

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ABSTRACT: This paper is concerned with the study of scene text detection and recognition from blurry natural image scene In digital imaging, it's a challenging task to restore a clear image from a single motion-blurred image due to camera shake. E.g. includes image retrieval, comparative studies of different images, as well as the tool that aid visually impaired individuals to access the pictorial information. Particularly when we use handheld cameras to capture natural scene images, a general problem, i.e., blur, frequently happens. There are several techniques available for text detection and recognition. For representation of the text and non-text fields, a string of text-specific multi-scale dictionaries (TMD) and a natural scene dictionary is used separately. The TMD-based text field reconstruction makes easier to deal with the different scales of strings in a blurry image effectively. A lot of work has been done for detecting text in images and a lot has to be done. In this survey, extend an existing end-to-end solution for text detection and recognition in natural images. This paper compares two filters on the measures of peak signal to noise ratio & mean square error. In this paper four types of noises(salt & pepper noise ,white Gaussian noise, speckle noise and Poisson noise) are used and image de-blurring performed for different noises by various filters. further results have been compared for all noises. It is observed that for Speckle and White Gaussian noise Weiner& for other noises median filter has shown the better performance results.

KEYWORDS: Scene text, text-specific multi-scale dictionaries (TMD),Text Localization , Non-uniform de-blurring, Noises, Filters.

I. INTRODUCTION

In digital imaging, it's a challenging task to restore a clear image from a single motion-blurred image due to camera shake. Motion blur caused by camera shake has been one of the prime causes of poor image quality in digital imaging, especially when using telephoto lens or using long shuttle speed. In past, many researchers have been working on recovering clear images from motion-blurred images. Here face the problem of recovering the clear scene text by exploiting the text field characteristics. A series of text-specific multi-scale dictionaries (TMD) and a natural scene dictionary is learned for separately modeling the priors on the text and non-text fields.

Taking handheld photos in low-light conditions is challenging. Since less light is available, longer exposure times are needed – and without a tripod, camera shake is likely to happen and produce blurry pictures. Increasing the camera light sensitivity, i.e., using a higher ISO setting, can reduce the exposure time, which helps. But it comes at the cost of higher noise levels. Further, this is often not enough, and exposure time remains too long for handheld photography, and many photos end up being blurry and noisy .

Many de-blurring techniques are used to improve the visual quality of images, which also play an important role in text recognition and image understanding. At the point when catching characteristic scene pictures, particularly by handheld cameras, a typical antiquity, i.e., obscure, To enhance the visual nature of such pictures, de-blurring methods are sought, which likewise play a vital part in character acknowledgment and picture understanding.

Text detection existing methods are mainly divided into 3 types. They are mainly sliding window based method, connected component based method, and hybrid method. Sliding window based method also known as region based method here it uses a sliding window in order to obtain the region. In connected component based method it mainly uses connected component analysis to extract text. Combination of both sliding window and connected component method are used in hybrid method.

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Text recognition may be possible by several methods OCR, can be used for recognition purposes. Optical character recognition is used to convert text in images into editable text. It recognizes the character by optical mechanisms. Several other methods are available for recognition purposes.

It is a two-fold method. To start with, because of the assortment of content sizes in various content fields of a picture, propose a novel TMD based content field reproduction strategy to manage diverse sizes of strings in a foggy picture viably. The proposed model can consequently took in multi-scale lexicons from the preparation dataset of content fields, which is more adaptable and don't require complex sifting systems for fitting the content properties as in [4]. Second, use a piece-wise scheme as in [3] to estimate the multiple kernels on different text fields selected by a text localization method automatically. However, the main difference between our method and [3] is that needs to partition whole images into multiple regions, while our method only considers the text fields because mainly focus on scene text de-blurring. Such implementation helps to recover a more clear text in real cases, as illustrated in Fig. 1.

Figure 1: An example of the scene text de-blurring[1]

II. PROPOSED SYSTEM

Content is pervasive in characteristic scenes, e.g. boards, billboard, house numbers and motion picture blurbs. Characters and strings in normal scene pictures give imperative data to a wide range of uses, for example, setting recovery, partner route, help perusing, and scene understanding. State-of-the-art blind image de-convolution approaches have difficulties when dealing with text images, since they rely on natural image statistics which do not respect the special properties of text images. On the other hand, previous document image restoring systems and the recently proposed black-and white document image de-blurring methods are limited, and cannot handle large motion blurs and complex background. Propose a novel text image de-blurring method which takes into account the specific properties of text images. Our method extends the commonly used optimization framework for image de-blurring to allow domain-specific properties to be incorporated in the optimization process. Experimental results show that our method can generate higher quality de-blurring results on text images than previous approaches.

In pervasive picture securing, picture obscure brought on by camera shake every now and again happens, which prompts the sudden corruption of picture quality, and hence makes character acknowledgment and picture seeing more troublesome. To enhance the visual quality for such pictures, the scene content de-blurring has gotten impressive exploration intrigues. Scientifically, by accepting the movement obscure is movement invariant, the foggy picture can be demonstrated as:

$$B = K \otimes L + N, \qquad (1)$$

where B remains for the hazy perception, L is the idle clear picture and N speaks to the added substance white Gaussian clamor. Also, K signifies the obscure part, and $\otimes$ is the convolution administrator. Inside this setting, a definitive objective of this paper is to recuperate the sharp and clean content from the foggy perception B. In any case, the issue of de-blurring is intensely not well postured, subsequent to there are interminable answers for Eq. (1).

The test of visually impaired de-blurring has pulled in much consideration as of late, and different picture blind de-blurring strategies have been proposed [1]–[3] to vanquish the errand. Despite the fact that these strategies can give promising results to characteristic scene pictures, they are still unacceptable for content pictures. One reason is that the majority of them utilize the normal picture measurements rather than the attributes of content fields as regularized.

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On the other hand,[12] proposes a contentaware earlier for archive picture de-blurring, however it is not extremely hearty for general foggy characteristic scene content pictures. As of late, Cho et al. [4] propose a powerful content picture de-blurring strategy taking into account three content particular properties. The strategy depends on the properties of content areas recognized by the stroke width change (SWT). Be that as it may, SWT is intended to distinguish content in clear pictures, the exactness of which may diminish or even come up short when connected to foggy pictures.

In this work, proposed a strong scene content picture de-blurring technique utilizing Content particular Multi-scale Word references, specifically TMD. The outline of our strategy is appeared in Fig 2. To begin with, by investigating the content and non-
content field qualities, take a characteristic scene word reference and a progression of content particular multi-scale lexicons to show the priors on the foundation scene and content fields individually.

- This stride is word reference learning highlighted by the red dashed rectangle.
- Second, run the cutting edge content confinement strategy to separate content fields from non-content ones.
- Third, in view of TMD and the regular lexicon, develop the committed priors for certifiable content and non-content fields.Therefore, improve the cost capacity to appraise the obscure bit and the idle picture.
- The last step will rehash until the obscure piece unite.

Note that the content fields after merges in the uniform de-blurring step should be non-consistently de-blurred as appeared in Segment II-D, where the non-content field won't on account of,concentrate on content fields de-blurring in this paper. Main: A genuine foggy scene picture from [1]. Base: Close-ups of de-blurring aftereffects of various content fields of the picture utilizing spatially fluctuating strategy. Note that these two de-blurred content fields have distinctive obscure portions as appeared in base and the outcome exhibits that it is uncalled for to evaluate a uniform piece for the whole picture. More subtle elements can be found in Fig.1 blur part merge.

A.NATURE IMAGE DEBLURRING

Blind de-blurring has received considerable interests from the communities of image processing, computer vision and graphics. Most of the existing methods achieve good results by designing various priors for optimizing:

$$\arg\min_{L,K} \|B - K \otimes L\|^2 + \rho(K) + \rho(L), \qquad (2)$$

where the first term is to suppress the reconstruction error, *i.e.* the restored image should be consistent with the observation with respect to the estimated blur kernel $\boldsymbol{K}$. $\rho(\boldsymbol{K})$ is a regularization term, typically a l_1-norm or l_2-norm penalty. The de-blurred result depends largely on the (specifically) designed prior knowledge $\rho(\boldsymbol{L})$ of the latent image.

This work focuses on the de-blurring for natural scene text, which utilizes the priors about the text properties to boost the performance. Another line of researches try to make use of sparsity property of the latent image $\boldsymbol{L}$. Sparse representation has been extensively applied to many ill-posed problems in image processing, such as de-noising and restoration . from an image $\boldsymbol{X}$ can be described by a linear combination of a The main idea of sparse representation is that a patch $\boldsymbol{x} \epsilon R^n$extracted few atoms from a dictionary $\boldsymbol{D} \epsilon \boldsymbol{R}^{n\times k}(n << K)$ learned from the training data. Thanks to the representation power, sparse representation has also been successfully applied to de-blur natural images [5], [11].

Therefore, design the prior of scene text based on sparse representation in this paper for scene text image de-blurring. Extend the ordinary dictionary to a series of text-specific multi-scale dictionaries and a natural dictionary. As a result, based on which design

$$\arg\min_{L,K} \|B - K \otimes L\|^2 + \rho(K) + \rho_t(L) + \rho_n(L), \qquad (3)$$

dedicated priors to be more applicable to scene text handling.where the subscript t and n stand for text field and non-text field, respectively.

B.TEXT IMAGE DEBLURRING

Although numerous methods have been proposed for nature image de-blurring, there are few models specifically dealing with scene text cases. Qi *et al.*[6] use cepstral domain techniques for identifying the blur

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parameters, but it can only deal with images with 1D kernels, i.e. the camera is assumed to move along a straight line with a constant acceleration. Su *et al.* [7] estimate blur parameters by the constructed alpha channel map based on specific image characteristics. Nevertheless, this method is designed for document images only. Li *et al.* [5]propose a statistical method to estimate blur kernels from two-tone images. Chen *et al.*[12] advocate a content-aware prior for image de-blurring to handle document images.

The projected methodology iteratively estimates the latent scene text image with TMD and a nature scene wordbook till it converges to a stable resolution. The 3 inexperienced dotted rectangles square measure solely dead within the uniform stage.This methodology uses a text segmentation technique supported thresholding to notice text so estimates the latent image by a learned intensity relationship between the muzzy and therefore the clear document pictures. However, these 2 strategies square measure solely applicable to two-tone pictures and square measure less effective for sophisticatedtext pictures. In alternative words, they're onerous to be directly applied to scene text pictures. to beat this challenge.

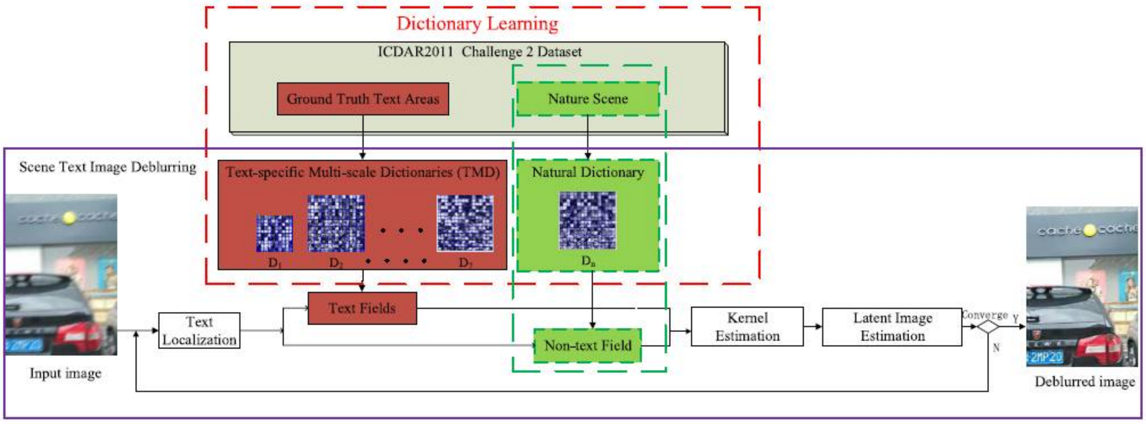

Figure2: Overview of our model

Cho et al. propose 3 text-specific properties supported SWT [15] because the text image priors:

- Text characters have high contrasts against background regions.
- every character features a near-uniform color.
- Background gradient values conform natural image statistics.

However, this methodology is extremely sensitive to the accuracy of SWT, that isn't effective once the muzzy characters square measure connected and noisy.Pan et al [8]. propose an efficient intensity and gradient based mostly L0 regularized previous for text image contain black pixels. However, the intensity-based L0 regularized previous would loss result when text image does not contain black pixel elements. That is, literature would degenerate a methodology once scene text in natural image isn't black. During this paper, have a tendency to introduce a rough text localization methodology, and iteratively refine the localization results to beat the limitation of SWT's sensitivity to muzzy pictures. additionally, have a tendency to use a series of text-specific multi-scale dictionaries to model the priors of the localized text fields. Moreover, our methodology is completely different from therein non-uniform blur kernels attribute to depth variation square measure thought of.

C. NON-UNIFORM BLUR

Early works target removing spatially invariant blur, the performance of that, however, typically degenerates or maybe fails to handle real pictures since the captured real blur kernels square measure are spatially variable owing to depth variation, camera shake, etc. for instance, in Fig. 1, 2 similar however completely different blur kernels and their associated clearer text fields square measure calculable. To model the spatial-varying blur, early relevant work as well as Ji [3], Cho[4] and Levin[10] model pictures as some piecewise uniform blur regions. Their performance depends on correct segmentation results on all regions within the image.

Our methodology solely needs to localize text fields as a result of our methodology focuses on scene text de-blurring. Additionally, our kernel estimation methodology is a lot of acceptable to scene texts because of the TMD. Some

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completely different approaches [10], [13]to model non-uniform blur are projected recently as a linear combination of various muzzy intermediate pictures captured by the camera on the motion flight. However, these strategies target handling 3D camera shakes on the price of presumptuous a relentless scene depth. Most of the text de-blurring strategies estimating one motion blur kernel for a complete scene text image. In distinction, have a tendency to aim to revive text pictures blurred by spatially variable blur kernels in several text fields.

D. DICTIONARY LEARNING FOR NON-TEXT AND TEXT FIELDS

Suppose , well-processed training data for text and non-text fields. Consequently, train TMD $\boldsymbol{D}_p^t$(where p denotes the scale index) and the natural dictionary $\boldsymbol{D}_n$, respectively, with respect to the text fields and non-text fields. The ICDAR 2011 Robust Reading Competition Challenge 2 dataset is widely used in scene text localization and word recognition in natural images, which contains 229 training images and 255 testing images including ground truth of text bounding boxes. The pixel number of the scene images in the dataset ranges from tens of thousands to ten millions, which has universality in all sorts of scene text to train dictionaries.

Training set $S = \{(\Sigma_{J=1}^{n} \mathbf{N}_J, \Sigma_{K=1}^{m} T_K)\}$,

1) Non-Text Dictionary Learning

$$\boldsymbol{D}_n = \arg\min_{\boldsymbol{D}_n, \mathcal{Z}_n} \|\mathcal{S}_N - \boldsymbol{D}_n \mathcal{Z}_n\|^2 + \lambda \|\mathcal{Z}_n\|_1, \qquad (4)$$

$$S_N = \Sigma_{J=1}^{n} N_J$$

2) Learning Multi-Scale Dictionaries

$$\boldsymbol{D}_t^p = \arg\min_{\boldsymbol{D}_t^p, \mathcal{Z}_t} \|\mathcal{S}_T^p - \boldsymbol{D}_t^p \mathcal{Z}_t\|^2 + \lambda \|\mathcal{Z}_t\|_1, \qquad (5)$$

$$S_T = \Sigma_{K=1}^{m} T_k$$

Where$\mathbf{N}_j$ is a nature scene image and $\mathbf{T}_k$ is a bounding box of the text field,$\mathbf{S}_N$ is the natural image in training set **S**, $\mathbf{S}_T$ is the text image in training set,Z_n is the set of sparse coefficients, $\boldsymbol{\lambda}$ is the parameter controlling the weight of the sparse term.

WHITE GAUSSIAN NOISE

White Gaussian noise is independent at each pixel and signal intensity. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel.

SALT-AND-PEPPER NOISE

An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions This type of noise can be caused by dead pixels, analog-to digital converter errors, bit errors in transmission, etc. This can be dark/bright pixels.

SPECKLE NOISE

Increase in power of signal and noise introduced in the image is of same amount that is why speckle noise is termed as multiplicative noise.

POISSON NOISE

Poisson noise, is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and the independence of photon detections.

MEDIANFILTER

The median filter is a non-linear digital filtering technique. It proves to be best in removing salt and pepper noise and. Median filter erases black dots called the pepper and fills in white holes in the image, called salt. It better works than mean filter by preserving sharp edges. It simply replaces each pixel value by the median of the intensity level in the neighborhood of that pixel.

WEINER FILTER

The wiener filter provides a solution of signal estimation problem for stationary signals. It also provides successful results in removing noise from photographic image. The design of the filter is distinct.

III. EXPERIMENTAL RESULTS

In this section, conduct the experiments on both synthesized and real data to demonstrate the efficacy of the proposed method, and compare it to the state-of-the-arts. By using different noises with different filters the performance evaluations are observed& employ the peak signal-to-noise ratio (PSNR) and mean square error(MSE).

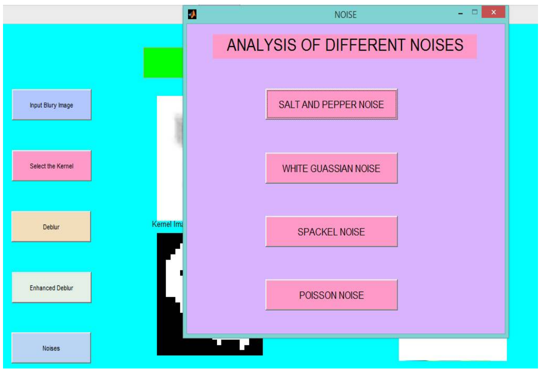

Figure 3: Analysis of different noises

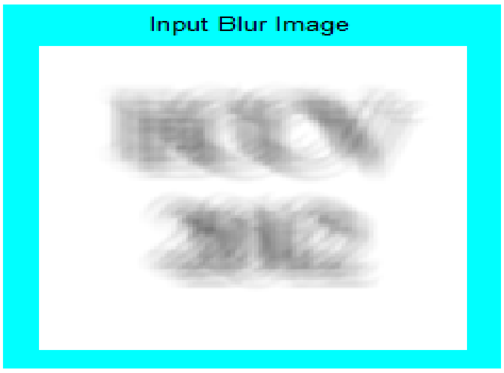

Figure 3.1: Input Blur image

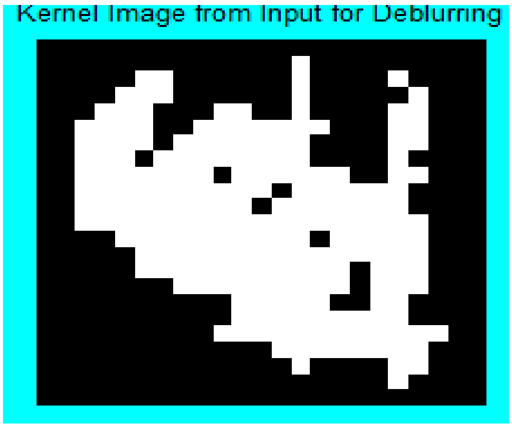

Figure 3.2: Kernel image

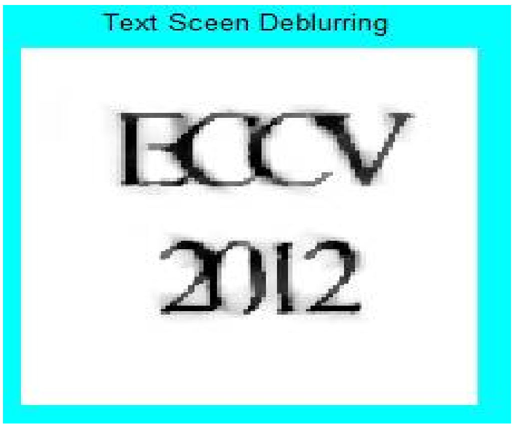

Figure 3.3: Text Scene De-blurring

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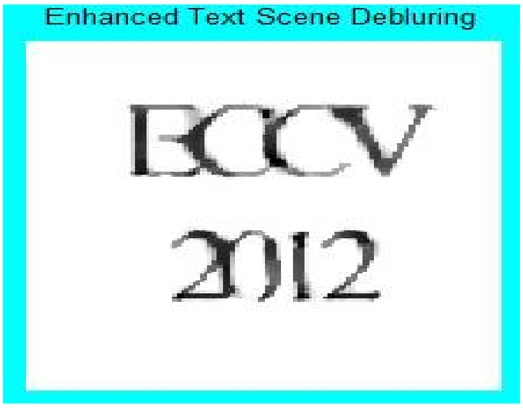
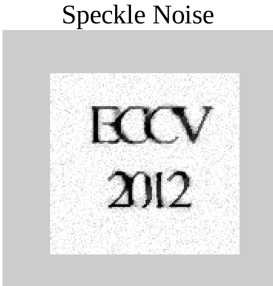
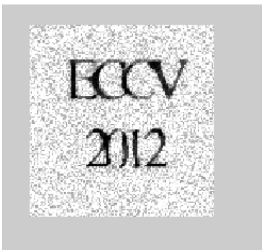


Figure 3.4: Enhanced Text Scene De-blurring

S.NO	NOISE IMAGES	FILTERS
1	White Gaussian Noise 	Weiner filter 
2	Speckle Noise 	Weiner filter 
3	Poisson Noise 	Median filter 

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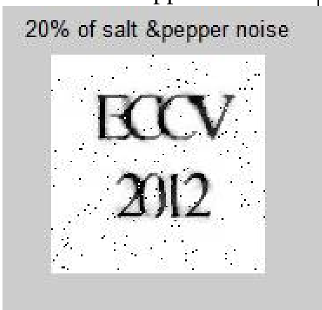
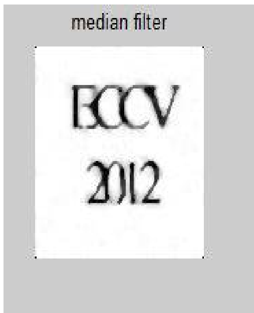
4	Salt and Pepper Noise 	Median filter 

3.5 EVALUATIONS OF PROPOSED METHOD

S.NO	NOISES	FILTER	PSNR	MSE
1	Salt & Pepper	Weiner	46.2	1.32
2	White Gaussian	Weiner	85.5	0.81
3	Speckle	Weiner	92.1	0.51
4	Poisson	Weiner	55.5	4.03

S.NO	NOISES	FILTER	PSNR	MSE
1	Salt & Pepper	Median	55.9	0.16
2	White Gaussian	Median	45.2	2.31
3	Speckle	Median	48.7	1.42
4	Poisson	Median	54.7	0.21

METHOD	PSNR	MSE
EXISTING METHOD	27.7	5.08

IV. CONCLUSION& FUTURE WORK

In this proposed a novel technique for the errand of scene content picture de-blurring by exert the qualities of the content fields. Our strategy utilizes the content limitation technique to find the content fields, and after that take preferences of the TMD and the regular word reference, prepared on the content and non-content patches, to recuperate the inert picture. The lexicon based strategy is more broad and adaptable in demonstrating the scene content properties than the specially appointed techniques in displaying picture priors, and is more vigorous to commotions.

Also, in light of the fact that the obscure showing up in genuine situations is not really a flawless spatial-invariant movement obscuring, our non-uniform strategy on every content field can better recuperate clear scene writings. Through these strides, perform broad tests on both the manufactured and genuine information, which exhibit the

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specific change over the condition of human expressions. Take note of that the bits of content fields in our non-uniform stage are introduced in view of uniform de-blurring, which makes our model have unassuming impact when the parts in various content fields are essentially shifting. In future work, this will outline more explained piece-wise de-blurring model to take nearby confirmation and worldwide consistence for strong and precise estimation of portions for various content fields.

The image is de-blurred with four types of noise. For each of these images two parameters MSE & PSNR are measured.

a) For Salt & pepper and Poisson noise, Median filter give better performance.

b) For Speckle and White Gaussian noise, Weiner filter give better performance.

The proposed method is applied to constant images. Further this may be extended to videos or moveable images.

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