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A Survey on Blind De-Blurring of Digital Image

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Abstract

Nowadays, huge digital images are used and transferred via the Internet. It has been the primary source of information in several domains in recent years. Blur image is one of the most common difficult challenges in image processing, which is caused via object movement or a camera shake. De-blurring is the main process to restore the sharp original image, so many techniques have been proposed, and a large number of research papers have been published to remove blurring from the image. This paper presented a review for the recent papers related to de-blurring published in the recent years (2017-2020). This paper focused on discussing various strategies related to enhancing the software's for image de-blur. The aim of this research is to help researchers to understand the current algorithms and techniques in this field, and eventually may developing new and more efficient algorithms for enhancing blurred images.

Keywords: Blur, Digital Image, Filters, Motion blur, PSF.

دراسة استقصائية حول الإزالة العمياء للضباب من الصور الرقمية

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الخلاصة

تستعمل الصور الرقمية في الوقت الحاضر بأعداد ضخمة وغالبا تنقل عبر الإنترنت، وهي تعتبر المصدر الرئيسي للمعلومات في العديد من المجالات في السنوات الأخيرة. وتعد الصورة الضبابية واحدة من أصعب التحديات الشائعة في معالجة الصور، وهي تنتج عن حركة الكائن أو اهتزاز الكاميرا. تعتبر عملية إزالة الضباب العملية الرئيسية لاستعادة الصورة الأصلية الواضحة، لذلك تم اقتراح العديد من التقنيات في هذا

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المجال، وتم نشر عدد كبير من الأوراق البحثية لإزالة الضباب من الصور الرقمية. تقدم هذه الورقة مراجعة للأوراق البحثية المنشورة في المجلات العلمية العالمية حول تقنيات إزالة الضباب من الصور للفترة من 2017 إلى 2020. وتم التركيز على مناقشة الاستراتيجيات المختلفة المتعلقة بتحسين الصورة الضبابية وتسليط الضوء على أحدث الأدوات المستخدمة في إزالة ضبابية الصورة، والتي قد تساعد الباحثين على فهم الخوارزميات الحالية والتقنيات في هذا المجال، وفي النهاية تطوير خوارزميات جديدة وأكثر كفاءة لتحسين الصور غير الواضحة.

1. Introduction

Modern imagery sciences, including photography, astronomical imagery, medical imaging, and microscopy, have evolved well over recent years and many advanced techniques have emerged. These advances have allowed images to be acquired at higher speeds plus higher resolution. High-resolution techniques can lead to degrader acquired image quality, which is an example of the blur and the subject of this article. The effect of image deblurring is effectively a clear image when eliminating distortion and blur. Blurring can take place because of several factors such as noise, dust, atmosphere, camera movement, object movement, etc. [1].

Image blurring is the primary cause of image loss, and the deblurring image is a common research concern in field of image processing. Blur image restores, i.e. image deblurring is a process in which latent sharp images are the conclusion, without enough details on the pattern degradation. De-blurring methods are known as non-blind and blind images. In the state of blind de-blurring, the blurring kernel is unknown while in the form of non-blind, previous knowledge of the blurred kernel and related parameters require [2].

In this paper, some types of blur that lead to image degradation and techniques for removing blur will be discussed. The rest of the paper includes types of blurring in section two, while the deblurring technique is introduced in section three. Section four focuses on literature review where there are several previous and related papers will be discussed. In section five some of performance measures are presented. Before section seven of the conclusion, there are some of comparison tables are introduced in section six.

2. Blur

Blur can be characterized as an undesirable transition to the original image for several reasons, such as camera-to-object movement, atmospheric turbulence, camera focus, fog, etc. In blurring, the strength of the edge decrease and smoothly transition from one color to another. Blur is the situation that can't perceive all the image content. The following are common blur types:

2.1 Average blur

Average blur affects the entire image. It can be spread horizontally and vertically, and calculated by a circular averaging of radius R that has evaluated by equation 1:

$$R = \sqrt{g^2 + f^2} \tag{1}$$

Where g represents the horizontal blurring, f represents the vertical blurring, and R represents the radius of the circular medium blurring [3].

2.2 Gaussian blur

Using Gaussian function in image processing can cause to blur the image (also Gaussian use for image smoothing). The pixels weights in the Gaussian blur are not equal and their values depend on the Gaussian bell-shaped curve; they decrease from the kernel center to the edges. The Gaussian blur effect is a filter that incrementally mixes a particular number of pixels, following a bell-shaped curve Gaussian blur relies mainly of the slandered deviation. The equation of a Gaussian function within one dimension is [4] [5]:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \tag{2}$$

Where σ is the standard deviation of the distribution and x is the location indices.

Where the equation of two-dimension results from two Gaussians in two dimensions, one in every dimension:

$$G(x,y) = \frac{1}{2\pi\sigma^2}\, e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

Where σ is the standard deviation of the distribution and x and y are the location indices.

2.3 Motion blur

Degradation of an image when relative motions between camera and target occur during image capture called the motion blur. The relative movement could differentiate several forms of motion blur between the recorder and the scene. This may be a transition or rotation or sudden shift in scale or a few variations [6].

2.4 Out focus blur

Blurring may occur when the object in an image is outside the depth of the camera through exposure. For example, if a camera images a 3-D scene display on a 2-D image plane, certain parts of the scene are focused while others aren't.

2.5 Atmospheric Turbulence blur

One of the common sources of distortion that affect an image is atmospheric turbulence. It occurs due to random variations in the medium's reflective index between the object and the imaging system, and it occurs in the imaging of astronomical objects. Blur presented by atmospheric turbulence relies on several factors such as temperature, wind speed, and exposure time. For example, stars in outer space viewed through telescopes appear blurred since the Earth's atmosphere degrades the image quality [3], [4].

3. Deblurring Techniques

Deblurring is a technique to remove artifacts from images that blur. Image deblurring can broadly divide into two classes, specifically blind and nonblind deconvolution. The blurry kernel Point Spread Function (PSF) is commonly supposed to be shift-invariant for both approaches. If we know or give the PSF, then this is called non-blind deconvolution, otherwise called blind deconvolution [7]. Image techniques can be shown in Figure 1.

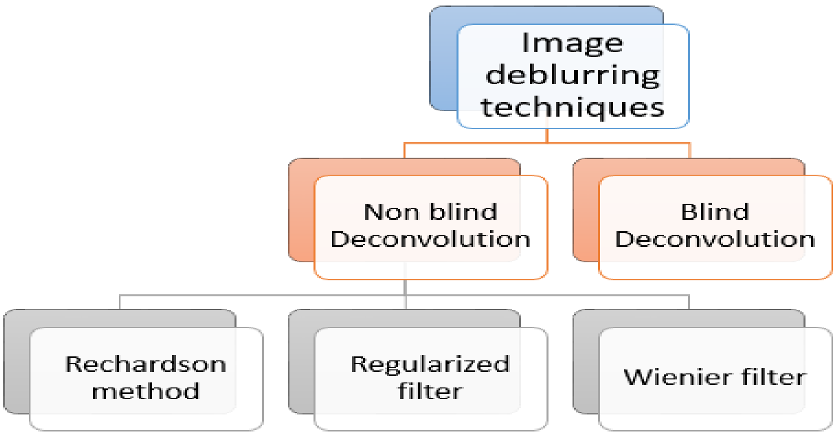

Figure 1- Image deblurring techniques [4]

3.1 Deblurring Images based on Non-Blind Deconvolution

Deconvolution technology is a process based on mathematical algorithms that are employed to invert the convolution effects in an image. This method is commonly employed in image processing and signal processing. In the Deconvolution process, the recovery process has previous knowledge of the degradation process, i.e. PSF is known [3].

3.1.1 Non-Blind Deconvolution Methods:

A. Deblurring Image Utilizing the LUCY RICHARDSON Algorithm (L-R Algorithm)

The Richardson–Lucy Deconvolution algorithm (also known as Lucy Richardson Deconvolution) is a popular image restoration technique. Initially, Leon Lucy and William

Richardson derived based on the theorem of the Bayes in the early 1970s. This approach is defined as a nonblind deconvolution because the PSF used to blur the image must be identified. It is also an iterative process [8]. The L-R algorithm can efficiently be used when the PSF well-known, but there is little or no noise information available. Using the iterative, accelerated, and damped L-R algorithm to restores the blurred and noisy image. The addition optical device properties (e.g. camera) may use as input parameters to enhance image restoration efficiency. The L-R algorithm works according to the following steps:
1- Read the image.
2- Emulation blur, noise.
3- Replace Blurred, Noisy Image.
4- Repeat explore that Restoration.
5- Control Noise Amplification via Damping [4].

Advantage of L-R algorithm

1- L-R approach maintains energy global and local during the whole iterate. Thus, neither the restored image nor any portion (important) of it would look much clearer or darker than the blurred vision.
2- When PSF is not precisely known, and only its estimate is available, the images restored are robust to small changes or errors in the PSF.

The disadvantage of the L-R algorithm

1- The R-L method creates ringing objects because it is vulnerable to the miscalculation of the kernel.
2- R-L algorithm will not restore images degraded by a convolution kernel that is not a valid PSF [7].

Figure 2- Deblurring images using Lucy Richardson [4]

B. Deblurring Images Using Wiener Filter

Wiener Filter works fine in the appearance of noise. Wiener Filter serves as a filter for all passes. The power spectrum for white noise is the same as the variation of noise. The Wiener Filter, which minimizes the average square error, can accommodate both arbitrary and degrading noise. Wiener Filtering performs an optimum balance between noise smoothing and reverse filtering. It eliminates additive noise and concurrently reverses the blurring. Since the Wiener filtering requires the reverse filtering stage, the noise amplifies if the blur filter does not invert [7].

Steps of implemented Wiener Filter algorithm are:
1- Read the image.
2- Emulation a motion blur.

3- Restore the blurred image.
4- Emulation blur, noise.
5- Restore the blurred image, noisy image.
6- Emulation blur, 8-Bit quantization noise.
7- Restore the blurred, quantized image.

Advantage of Wiener filter

1- Wiener Filter performs fine when the variation is tiny if the image has Gaussian white noise.

2- Wiener Filter is useful when the PSF is well-known or can be a fine estimate, and a reasonable noise estimate is possible.

The disadvantage of Wiener filter

1- The original image can only recover perfectly if no noise is present, and the PSF is known.

2- Wiener Filter is not working fine if the PSF not available [4].

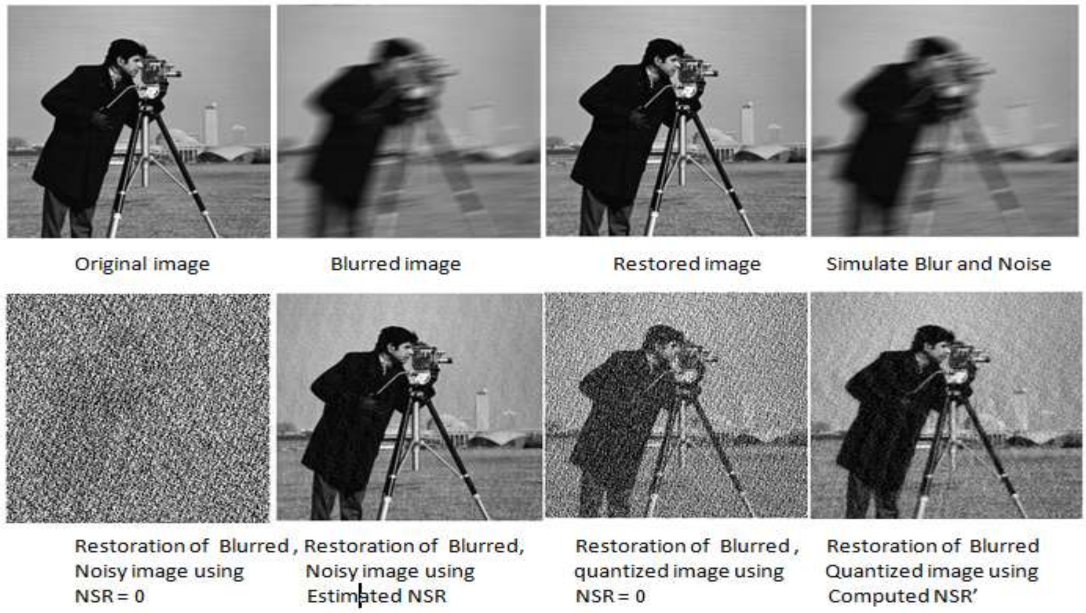

Figure 3- Deblurring images using Wiener Filter [4]

C. Deblurring Images Using a Regularized filter

A regularized filter or called constraint least-square filter is best utilized when limitations such as smoothness apply to the recovered image and considerably less knowledge of additive noise. The blur and noisy image restore via a Constrained Least Square restoration algorithm, which utilizes a Regularized Filter. The outcome of Regularized restoration nearly like Wiener Filtering, but with different techniques. In Regularized Filtering, little prior information requires to implement restoration. The Regularization filter repeatedly is selected to be a discrete Laplacian. Regularization filter may be understood as the estimation of a Weiner filter [1].

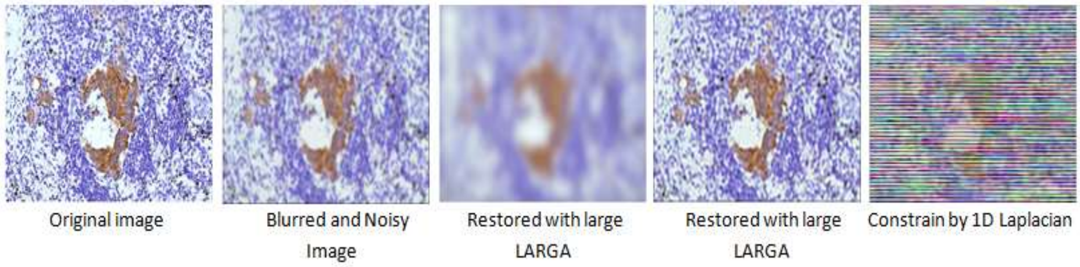

Figure 4- Deblurring images using Regularized filter [4]

3.2 Deblurring Images Using Blind Deconvolution

Two kinds of blind deconvolution approaches are available. They are projection-based blind deconvolution and extreme probability restoration. In the first method, the actual image and PSF are simultaneously restored. This starts by suggesting initial estimations of the original image and PSF. First, find the PSF estimation, and then find the image estimation. This cyclic method iterated till a predefined convergence standard satisfy. The benefit of this method is that it seems strong to the imprecision of support size, also this way is not affected by the noise, the problem with this way is not unique. The disadvantage of this method is the probability of having an error in local minima. In the second method, the maximum likelihood is determined for the parameters such as PSF and covariance matrices. Since the PSF estimation is not unique other measurements such as PSF size, symmetry, etc. can be considered. The benefit of this method is that it has low computation complication and also assistance to achieve a blur, noise, and power spectra of the original image. The disadvantage of this method is converging the determined cost function to local minima.

There are other blind techniques like Neural Network (NN). In Neural networks, different kinds of learning algorithms are combined that are inspired and taken by biological neural networks and are used to calculate or approximate functions that can depend on a very large number of unknown inputs. Neural Networks are typically offered as regulations of interconnected sets or single "neurons" that can compute input values and have the ability to machine learning and pattern recognition. The system uses algorithms in its programming to evaluate the organization and control of its work. The Neural network does not need any previous information as it is utilized to know the blurred in the hidden layer during the learning process. The real knowledge of signals, dots, and blurred patches is known by estimating the actual link between a degraded dot in the provided blur image and the analogous dots in the real image [1].

4. Literature Review

In this section, we present a study on various techniques of image deblurring.

Zhou et al. presented an enhanced approach to estimating the blurring parameters of the motion deblurring algorithm for a single-image restoration based on PSF in the frequency spectrum. They then modified the Radon Transform (RT) to the blur angle assessment scheme using their suggested variation versus the angle curve. Finally, the auto-correlation array is used to estimate the blur angle via calculating the distance among the connected troughs. High precision for both blur angle and length can be achieved from this method. On the other side, this method is not a practical solution for the nonlinear and nonuniform motion blur problem [9]**.**

Zhang and Zheng introduced a blurred parameter recognition algorithm with PSF. The current algorithm merges the Fourier spectrum of the image with edge detection based on phase-consistency. The blurred angle is identified by defining the trend of the edge of the bright strip center. Then bilinear interpolation is employed to produce the sub_pixel image of the spectrum, measure the distance among the dark strips, and estimate the blurred length. This method produced higher precision of blurred angle and blurred length, better stability, and correctly detect blurred parameters of blurred images [10]**.**

Khan and Yin presented a new blind deblurring schema for images that were distorted via arbitrary PSFs. It depends on a genetic algorithm and employs the Blind Image Spatial Quality Evaluator (BRISQUE) measurement, which is a suitable function for arbitrarily formed PSF estimate. This method is effective in estimating PSF for arbitrarily shaped and parametric PSFs for artificially blurred images and well estimates the blurring kernel for real-life blurred images resulting from camera handshake. The challenge and disadvantage of current research, that still unable to deblur the complicated camera handshake PSFs, especially for real-life blurred images [11].

Y. Elmi et al. presented an approach for estimating parametric PSF. This approach can be used to estimate the linear motion blur vector parameters. This method is used to determine the angle and length for the motion blur vector in a single image to produced PSF for deblurring. This blind approach takes small vectors in all trends and deblurs with the PSF of those candidate vectors. A no-reference quality measurement metric assesses the goodness of the deblurred image. The no-reference image quality metric assesses measure the edge degradation in the sharpness, and the quantity of artifact produced from saturated pixels, in the deblurred image. In the next iteration, the unacceptable blurring caused by motion vectors is eliminated. The approximation has been enhanced by extended the length of rest vectors, and the same procedure is continued recursively. The method continues until only one vector remaining as the estimate for movement vector blur. In this method there is no additional hardware is needed, fully automatic, and doesn't require operator intervention, use the blurred image for estimating PSF only, improved movement accuracy blurred vector parameters, and less computational time [12].

X. Y. Yu and W. Xie presented a new blind image deblurring approach that merging the notable edge-structures and the elastic-net regularization. The notable edge structures are chosen from the intermediate image and employed to direct the blurred kernel estimation. Then the elastic net regularization and edge structures are used to more determine the latent intermediate image, maintain the predominant edge, and eliminate a slight texture to estimate the kernel better. It is an effective method on some image datasets. The drawback of this method is that the calculation of the kernel has a lot of noise or outliers because the blurred image has low variance and low accuracy [13].

Feng et al. proposed new measures to optimize edge extraction and to decide suitable width and weights for the edges extracted to improve their application in the deblurring method. The authors first estimate the likelihood of pixels on the edges, they used a stochastic forest structure edge detection tool. Next, they proposed a two-stage threshold method for edge detection, one to detect robust boundaries globally, and the other to detect clear boundaries in locally located regions. Then edges with acceptable width are produced, and proper weights assign to them for deblurring. They refresh the deblurring algorithm with our observed edges. This proposal improves the deblurring performance; mostly, it is fine to suppress the ringing artifacts. This method works well comparing with existing methods, it can improve the deblurring result and achieve equal or even better results than methods based on learning [14].

Kapuriya et al. process a single image to restore objects blurred (due to object movement) by multidirectional motion blur. They combine the Radon Transform (RT) and Laplacian of Gaussian (LoG) to detect local blur angle. The estimate of the probable blur direction in a blurred image is determined by the RT and gradient operators. Also, they proposed to use RT with LoG to detect locally the blur angle at each pixel. The advantage of this method that is best among the other existing methods for detecting blur angle locally and it could be used for various non-uniform object motions [15].

Zhu et al. introduced a blind deblurring method basis on a local rank of a single image. Firstly, the adaptive threshold segmentation was implemented on the traditional local rank transform, which subsequently created a new blind image deblurring model. Then, the blurred kernel is determined alternating iterations by using the half-quadratic splitting method. Lastly, the desired latent image is provided by a linear merging of the Hyper-Laplacian model and the total variation-l2 model, the weights are determined from local adaptive ranks. The benefit of this method is that the blur kernel can be reliably measured and ringing objects in the image effectively removed [16].

Shen et al. presented a Convolution Neural Network (CNN) architecture which included multiple deep characteristics. They solved the issues with deblurring transfer learning via a multi-task embedding network, and the suggested approach proposed is successful in restoring implicit and explicit structures from blurred images. Moreover, by incorporating perceptual characteristics in the deblurring phase and using an adverse generative network, they create a new way to deblurring the face images with the reservation of more facial characteristics and information. This method is effective for deblurred for face detection and recognition [17].

Wang et al. presented addressed the problem of restore images with a knife-edge function and optimal Wiener Filtering window. In the suggested process, the movement-blur parameters are first determined, and the optimal window is created. The knife-edge function detected is then used to get the device deterioration function. Lastly, they implement Wiener filtering to obtain the restored image. The advantage of the suggested method that the restored image enhances the resolution and the contrast parameters with precise information and no visible ringing effects [18]**.**

Nagata et al. presented a blind deconvolution approach to estimation PSF and the latent image alternately. They implement a gradient reliability map which allows the selection of right edges for PSF estimation and an energy function that enables convergence cases to be decomposed. This method enhances restored performance by reducing noise, adversely affecting estimation. The advantage of the proposed method is an accurate estimate PSF and perfect image restoration [19].

Abbass et al. presented a new computational method to solve the blind deconvolution problem by incorporating homomorphic scope tools and outlier treating methods into blurred images. Many methods for blind image deconvolution use complicated algorithms and can therefore contribute to unnecessary overhead when the blurred kernel is computed. The blurred image is decomposed by the homomorphic phase into two key components. It is understood that the homomorphic domain can be forced on images via the logarithm process that divides the image into the lighting and reflectance components. The reflectance component includes the most notable specifics of the image, while the lighting component often has unnecessary information on the image. This method extracted accurately motion blur kernels and removing redundant details in the given image [20]**.**

Abbadi et al. presented a new deblurring algorithm that combined deblurring techniques with a suggested new filter for enhancing image blurring removing techniques. The suggested procedure combined the Laplace filter with a Markov basis for edge detection, it is modified slightly to become suitable for color images. The proposed algorithm is based on combining the proposed filter with several deblurring techniques which are leads to improve the deblurring performance for several methods. Besides, the deblurring performance for both color and gray images is increased by using a median filter. This work has a good enhancement for image deblurring compared with other techniques [21]**.**

Shah & Dalal presented a blind motion deblurring algorithm, which determines the motion blur parameters (length, angle) in a transformed cepstrum domain by a blind no-Reference Image Spatial Quality Evaluator (BRISQUE) employed to tuning PSF parameters. During the deblurring process, ringing objects are produced. The updated R–L algorithm with a graph-cut-based weight computation is introduced to achieve a good ringing decrease estimate of the unblurred image. The approach contains choosing the various weights for edges and smooth areas so that R-L repeats can minimize the ringing impact. This technique estimates the PSF parameters in noiseless and in low noise conditions accurately and can handle high-level noise using denoising [22]**.**

Askari Javaran et al. introduced a blind deblurring method that focused on removing the local motion blur automatically, for that the blurred region is detected and extracted. It suggested an optimization problem as a maximum-a-posteriori (MAP) which determined the blurred kernel and the latent image concurrently. In the MAP, an efficient previous image is employed based on both the image's first and second-order gradients. This previous helps to rebuild salient edges in the latent middle image to provide accurate edge information for kernel estimation. it's efficient for both global and local deblurring. The disadvantage of the suggested method is that it uses deblurring of images only when the blur type is linear motion [23]**.**

Chang et al. presented a new single image deblurring algorithm for non-uniform motion blur images blurred by moving objects. Firstly, a uniform defocuses map method was introduced for measuring motion blur amounts and trends. These blurred areas were then used to estimate PSF simultaneously. Finally, a quick deconvolution algorithm is employed to restore the nonuniform blur image. this method is effective for any motion blur, but it is shadows tend to cause the algorithm to detect blurred objects incorrectly [24]**.**

5. Performance Measuring Tools

Some of the performance tools used to evaluate deblurring techniques introduced in this section:

- **Root Mean Square Error (RMSE)**

Root Mean square Error is a kind of performance measurement method employed very widely to calculate the variations among the expected value by an estimator and the real value. The Root Mean Square Error is the square root of the Mean Square Error essentially [25].

$$RMSE(\hat{\theta}) = \sqrt{MSE(\hat{\theta})}$$

- **Peak Signal to Noise Ratio (PSNR)**

PSNR is one of the most common measures of distorted image performance. It calculates the distortion between the reference image pixels and corresponding distorted image pixels. The PSNR of the m*n image is defined as: [26]

$$PSNR = 10 * log_{10} \frac{L^2}{MES}$$

Usually, when PSNR is increasing the quality of the restoration is increased. That is, an optimal PSNR is an infinity [9].

- **Structure Similarity Index Method (SSIM)**

The Structural Similarity Index is a model focused on perception. In that process, image deterioration in structural information is regarded as a shift in perception. The phrase structural information focuses on the highly interdependent pixels or pixels that are spatially closed. These highly interdependent pixels indicate more relevant information about the visual objects within the image domain. SSIM assesses the perceived goodness of image and video. The similitude between the two images is calculated: the pristine and the retrieved. The SSIM index evaluates a test image X with respect to a reference image Y to quantify their visual similarity. The general formula is:

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma}$$

Where α, β and γ are parameters that define the relative importance of each component, and l, c, s represents luminance, contrast, and structure:

$$l(x,y) = (2\mu_x\mu_y + C1)/(\mu_x^2 + \mu_y^2 + C1)$$
$$c(x,y) = (2\sigma_x\sigma_y + C2)/(\sigma_x^2 + \sigma_y^2 + C2)$$
$$s(x,y) = (\sigma_{xy} + C3)/(\sigma_x\sigma_y + C3)$$

Where x, y two color image, μ_x, μ_y mean of images x and y, σ_x, σ_y standard deviation of images x and y, C1, C2, and C3 are constants introduced to avoid instabilities when average pixel value ($\mu_x^2 + \mu_y^2$), standard deviation ($\sigma_x^2 + \sigma_y^2$), or $\sigma_x\sigma_y$ is close to zero. SSIM (x, y) ranges from zero (completely different) to one (identical patches) [24], [25].

- **Structural Dissimilarity (DSSIM)**

This is the structural dissimilarity metric which is deduced from SSIM as follows:

$$DSSIM(x,y) = \frac{1 - SSIM(x,y)}{2}$$

The greater values of SSIM and DSSIM refer to the greater similarity between images[27].

- **Features Similarity Index Matrix (FSIM)**

Feature Similarity Index process sets the characteristics and the similarity calculation of both images. Two parameters need to be defined more explicitly to define FSIM. There are phase congruency and gradient magnitude [25].

6. Comparative Analysis

This section includes a comparison between deblurring techniques in terms of the advantages, disadvantages, procedures, and image quality measures like PSNR (Peak signal-to-noise ratio). Table 1 shows a comparative study among these methods. While Table 2 presents a comparison of several previous works. And finally, the performance of several methods is introduced in Table 3.

Table 1-Comparative analysis of existing methods

AUTHORS	PUBLISHED YEAR	METHOD	FEATURES	CHARACTERISTICS
W.Zhou et.al	2020	Radon transform , auto-correlation-matrix-based	blur angle estimation, a blur length estimation	Advantage: 1- high precision for both blur angle and length Disadvantage: 1-The nonlinear and nonuniform motion blur problem is not a practical resolution.
Zhang & Zheng	2020	Fourier spectrum characteristics, Phase Consistency, Radon Transform, Bilinear Interpolation	Detect motion blur angle, Estimate blur length.	Advantage: 1- Higher precision. 2- Better stability. 3- Correctly detect blurred parameters.
Khan & Yin	2020	genetic algorithm, Blind/Referenceless Image Spatial Quality Evaluator	arbitrarily shaped PSF estimation	Advantage: 1-Effective PSF estimates for arbitrarily shaped and parametric PSFs. Disadvantage: 1-A difficult task particularly for blurring images in real life.

Elmi et al.	2020	parametric PSF estimate, no-reference image quality metric	Estimation parameters of linear motion blur vector, Assessment of the deterioration of the goodness of the deblurred images.	Advantage: 1-No additional hardware is required. 2-Fully automatic and requires no intervention by the operator. 3- Use the blurred image to estimate PSF only. 4- Improved accuracy in movement estimation blurred vector parameters. 5- Lower computation time.
Yu & Xie	2020	Based on salient edge-structures, elastic-net regularization.	The estimation of the blur kernel, Estimate a latent image.	Advantage: 1- Effective on some image datasets. Disadvantage: 1-Since the blurred image has low variance and low accuracy, the calculated kernel has a lot of noise or outliers.
Feng et al.	2019	a random forest structure edge detection method, two-level thresholding approach	Estimate the probability of pixels on edges, Edge detection	Advantage: 1- Improve deblurring results. 2- Produce equivalent or even better results than learning-based methods.
Kapuriya et al.	2019	Radon Transforms, Laplacian Of Gaussian, directional derivative	Estimate multi-directional object motion blur parameters.	Advantage: 1- Best methods for local blurred angle detection. 2- It could be used for various non-uniform object motions.
Zhu et al.	2019	adaptive threshold segmentation, half-quadratic splitting method, hyper-Laplacian model, the total-variation-l2 model	Estimate blur kernel, Estimate a latent image.	Advantage: 1- Measurement the blur kernel correctly. 2- Suppress ringing objects effectively in the image.
Li et al.	2018	based on exemplars, multiple-size partition strategy, an exemplar matching criterion, regulation term	Deblurring traffic sign.	Advantage: 1- It is useful for deblurring traffic sign images. 2- Lower the time cost. 3- Achieve better accuracy. 4- Better the sparsity of the kernel. Disadvantage: 1- It needs to improve in real-time. 2- It isn't used to judge criteria for image blurred degree.

Table 2 -a comparative analysis of some previous deblurring methods [28].

SEQUENCE	AUTHORS	IMAGES	METHODS	FEATURES	RESULTS
1	Ratnakar Dash, Banshidhar Majhi.	Motion blur Image.	Gabor filter	Estimate the blur angle	Perform even in noisy conditions.
2	Xiaogang Chen, Jie Yang and Qiang Wu.	Blur Image.	Blind deconvolution	A rough calculation to a great degree under constrained and quick to detect noise.	Both out of focus images and complex motion images are re-establish by blur images.
3	Joao.P. Oliveira	Motion blur Image.	Modified random transforms.	Transforms integral function along a straight line.	Effectiveness was assessed by testing.
4	Sina Firouzi and Chris Joslin.	Motion blur Image.	Phase correlation	Motion estimation tool	Estimate the motion in transitions.
5	Zhiqiang Wei, Caiyan Duan, Shuming Jiang et.al.	Motion Blur Image, defocus blur Image.	Wiener filtering.	Divide foundation into parts	Its partition forcibly put an end to the noise but also weaken the artifacts of the images.
6	Binbin hao, Jianguang Zhu and Yan Hao.	Blur Image.	Total variation.	Calculate the regularization parameter for TV.	It identifies a new adaptive iterative forward-backward splitting (AIFBS) algorithm for TV image restoration.
7	Weisheng Donga and Lei Zhang.	Blur Image.	Adaptive sparse domain selection (ASDS) scheme.	It learns a variety of compact sub-dictionaries and assigns them accordingly.	It exceeds several state-of –the-art procedure in both PSNR and visual quality.
8	Justin Varghese, Mohamed Ghouse, Saudia Subash et.al.	Blur Image.	Adaptive fuzzy based switching weighted average.	For detection and filtering.	Determining weighted directional distances
9	Jishan Pan and Zhixun Su	Blur Image.	lL0-regularized approach.	A rough calculation of blur kernel.	To raise the robustness of kernel rough calculation.
10	J. C.Yoo et.al	Original image.	Blind wiener filter.	Restore the original image when there is no knowledge of power spectra of noise and original image.	Consecutive images generated from adding random noise.
11	Hui Yu Yuang	Motion blur Image.	Fast blur kernel estimation.	It can rapidly discover the better kernel from a group of kernels.	It quickly orders time and also maintain the image quality after deblurring.

Table 3-Comparing the performance of deblurring methods based on PSNR index.

SEQUENCE	AUTHORS	PUBLISHED YEAR	COMMENTS	PSNR
1	Shah & Dalal	2017	Noise free	36.6803
			Gaussian noise	33.093
2	Wang et al.	2018	motion blur	29
3	Nagata et al.	2018	-	30.87
4	Abbass et al.	2018	Gaussian blur	32.93875
			motion blur	31.67113
			out-of-focus blur	31.4011
5	Abbadi et al.	2018	wiener filter + new filter	34.67
			Regularized + new filter	47.22
			Lucy-Richardson + new filter	52.23
			blind algorithm + new filter	53.67
			wiener filter + new filter + median filter	45.24
			Regularized + new filter + median filter	56.14
			Lucy-Richardson + new filter + median filter	57.31
			blind algorithm + new filter + median filter	59.31
6	Feng et al.	2019	edge extraction	27
7	Zhu et al.	2019	-	30
8	Yu & Xie	2020	-	35.66
9	W.Zhou et.al	2020	-	78.31
			noisy circumstances	70.56

7. Conclusion

In this article, we present a review of the most modern methods for image deblurring. Many ways presented and compared (published in 2017-2020). In recent years, the majority of papers focuses on blind image deblurring algorithms. Furthermore, most algorithms focused on finding the PSF parameters. Simultaneously, blind deconvolution estimates PSF and sharp images, it does not have previous information on PSF, kind of a blur, and kind and amount of noise. Most of the papers discuss non-blind deconvolution in three common techniques: Lucy-Richardson algorithm, Wiener filtering, and regularized filter. The methods with high accuracy having a very complicated procedure for image deblurring. It is concluded that the important parameters to remove the motion blur are the motion angle and length, and from these parameters, all the researchers can create a de-blur filter. Fourier transform, radon transform, and Hough transform are the best tools to estimate the motion angle and length. The efficiency of de-blurring algorithms depends on the accuracy of estimation motion angle and length. There is no ideal algorithm in this field. We thought that the leading parameter in this field is the motion angle.

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