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Review of Single Blind Image Deblurring Techniques

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ABSTRACT

Digital images are an inseparable part of our everyday personal lives where we capture any moment for sharing with others, later viewing or in professional applications like remote sensing, medical imaging, surveillance, etc. The past decade saw an unprecedented increase in the availability of affordable, portable, and highly functional digital multimedia devices such as cameras, mobile-phones, digital recorders, etc. Due to this increased possibility of generating digital audio-visual content without constraints of time, location, and network has been possible [1]. Although on one hand, there is a plethora of devices that claim to deliver HD quality of images but that is true only for static images in an ideal setting, on the other hand there are images that are often blurred due to various reasons that prevents us from exploring the necessary details making feature extraction tasks such as object recognition, segmentation, alignment and stitching of images, 3D stereo reconstruction, self-navigating robots or cars, etc. difficult [2]. This review paper focuses on the study of different techniques of single blind image deblurring used for restoration & enhancement of blurred images.

***Keywords* —** Blur, blind deblurring, point spread function, priors, convolution neural networks, datasets, benchmarks, image quality metrics.

I. INTRODUCTION

Digital images find their application in almost every aspect of life. Some areas where digital images are professionally used are surveillance systems, medical field, remote sensing, pattern recognition, etc. as showed in Figure 1. Most of the times professional digital images captured in ideal settings are static or captured in automated fashion like in medical imaging where the patient is stable. But in other cases, very often digital images that are captured using handheld devices like mobile phone or digital cameras contain blur which can be due to various factors such as camera motion, motion of object, angle of camera, light exposure, etc. Blurring of an image is one of the major reasons for degradation of an image [3][4]. Image blur is an undesired artefact in digital images and prevents the accurate interpretation of scene or feature extraction as it causes loss of necessary detail [5]. Examples of types of blur identified in forensics include: Motion Blur, Gaussian Blur, Out of Focus blur, Atmospheric blur, etc [6]. In Figure 2 below, the number of people & the license plates could not be identified in the blurred images.

This paper is organized as follows. Section 2 justifies the need for writing this research paper. Section 3 defines the terms on blurring its types, deblurring, its classification and image deblurring techniques. Section 4 presents the review of literature in single blind image deblurring techniques. Section 5 presents the observations of the papers reviewed from different perspectives. Section 6 presents the concluding remarks.

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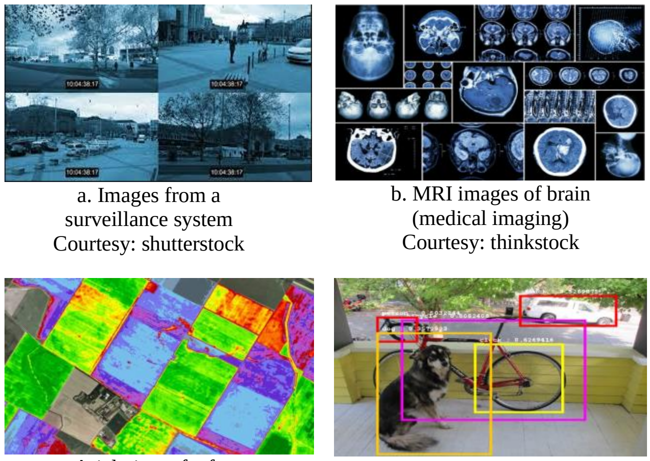

a. Images from a surveillance system Courtesy: shutterstock

b. MRI images of brain (medical imaging) Courtesy: thinkstock

c. Ariel view of a farm (remote sensing) Courtesy: geoawesomeness

d. Object Detection (pattern recognition) Courtesy: jetbrains blog

Fig 1. Real Life Applications of Digital Images

II. RATIONALE

Image deblurring, denoising & restoration has traditionally been a challenging problem in image processing. When images fail to achieve a desired level of quality with reference to its clarity and/or features present in it, a process called image restoration is applied to alleviate its quality. Poor quality input images pose problems for high level image processing task such as image classification, object recognition, and scene understanding. Image restoration has a rich literature where different techniques have been developed over time with promising results but the need for better, innovative and faster solutions still exits. The rationale behind reviewing single blind image deblurring techniques is to identify the research gap in the literature and contribute by proposing a solution in the near future.

III. BLUR DEFINITION

Blur is a historical problem for which solutions have been studied over a number of decades. Its root cause is the inability of an imaging system to focus on objects on an image plane at the same time, or relative motion between a camera lens and an object during exposure. The uncontrolled and varying conditions of forensic imagery can result in both of these causes being realized, and thus it is extremely common for both images and video to require some form of de-blurring within the sequence of enhancement operators applied to recover high-frequency information, and thus detail [8][9][10][11].

Figure 2a(left)-Blurred Images acquired from a CCTV surveillance camera
Figure 2b(right) - Blurred Images acquired from a video recorded on a mobile phone [7].

The blurred image can be expressed as: $G = H * F + N$
where, F is the original latent image, H is the point spread function (PSF); it controls the degree of distortion in the image, N is the additional noise that gets picked up during acquisition of the image and is responsible for corruption of the latent image, (*) is the process of convolution between latent image and PSF while G is the degraded blurred image [12].

A. Types of Blur:

Following are the different types of blurs encountered in the literature of image processing: gaussian blur, average blur, motion blur, box blur, out of focus blur, atmospheric blur [13][14][15]. Restoration tasks in image forensics usually identify motion blur and out-of-focus blur as the main source of image blurring. Motion blur occurs due to the movement of objects during the image acquisition process [16] or the movement of cameras at the time of the scene capturing [17]. Lens defocusing is the major reason for out-of-focus blur [18].

B. Deblurring - Definition, Types, Techniques

Deblurring is the restoration of images, a process of recovering an original image from the degraded image which has been blurred due to various factors mentioned above. The process of recovering original image from the blurred image is known as Deconvolution process.

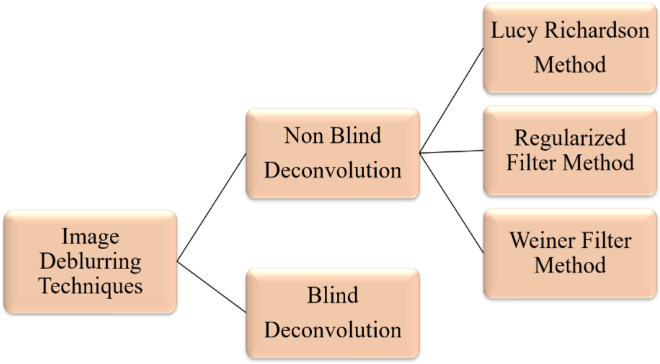

Fig 3. Types of Image Deblurring Techniques

Non blind Deconvolution is the process of estimating the latent image from a pair of latent & blurred image along with the knowledge of PSF such as motion PSF or Gaussian PSF, commonly used techniques are deconvolution using Lucy Richardson, Regularized Filter & Weiner Filter [20]. Blind Deconvolution is a technique that recovers the latent image from a single or a set of blurred images where the point spread function (PSF) type is unknown and hence involves estimation of the PSF and restoration of the latent image as the deconvolution is performed [21]. The process of image degradation is described in Fig 4.

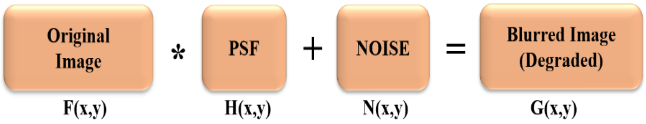

Fig 4. Image Degradation Model [22]

Analysis of various non-blind and blind deblurring techniques done by Yadav, Sudha et al [4], Devi, M et al [13] and Muthana, R et al [14] are tabled in Table 1 using the metric of Pixel Signal to Noise Ratio (PSNR) as metric. The following Table 1 gives a comparative analysis of the different deblurring techniques mentioned above using the metric of Pixel Signal to Noise Ratio (PSNR). The result of the analysis is visualized below in Fig 5. The analysis indicates that techniques in the category of non-blind image deblurring have low PSNR values while techniques in the category of blind image deblurring have high PSNR values, namely ADSD-AR gives highest PSNR value, followed by Neural Networks.

Table 1. Analysis of various Non-blind and Blind deblurring techniques done by Yadav, Sudha et al [4], Devi, M et al [13] and Muthana, R et al [14].

Method	**Yadav, Sudha et al [4]**			**Devi, M et al [13]**			**Muthana, R et al [14]**		
	Types of blur	**Perfor-mance**	**PSNR Ratio**	**Types of blur**	**Perfor-mance**	**PSNR Ratio**	**Types of blur**	**Perfor-mance**	**PSNR Ratio**
Blind deconvo-lution	Gaussian blur	Efficient	26.78	Gaussian blur	Efficient and good	26.77	Gaussian & Motion	Efficient	26.78
Lucy Richardson	Gaussian blur	Efficient	21.06	Gaussian blur	Efficient	21.05	Gaussian blur	Efficient	21.06
Wiener filter	Gaussian blur	Worst performance	17.05	Gaussian blur	Worst performan ce	17.07	Gaussian blur	Worst performance	17.05
Regularised filter	Gaussian blur	Efficient	20.1	Gaussian blur	Efficient	20.12	Gaussian blur	Efficient	20.1
Handling outliers	Gaussian	Efficient	21.9	Gaussian	Efficient	21.92	--	--	--
ASDS-AR	Gaussian	Very Efficient	31.2	Gaussian	Very Efficient	31.21	Gaussian	Very Efficient	31.2
Neural Networks	Gaussian Out-of-focus	Very Efficient	30.11	Gaussian Out-of-focus	Very Efficient	30.1	Gaussian Out-of-focus	Very Efficient	30.11
Hyper-spectral (PCA)	Hyper-spectra l image blur	Efficient	22.34	Hyper-spectra l image blur	Efficient	22.35	Hyper-spectra l image blur	Efficient	22.34
Motion density	Motion	Efficient	24.31	Motion	Efficient	24.3	Motion	Efficient	24.3

In general, blind deblurring techniques give better results than non-blind deblurring techniques. The PSNR is a metric which computes the peak signal to noise ratio between restored image and the original image, it is measured in decibels.

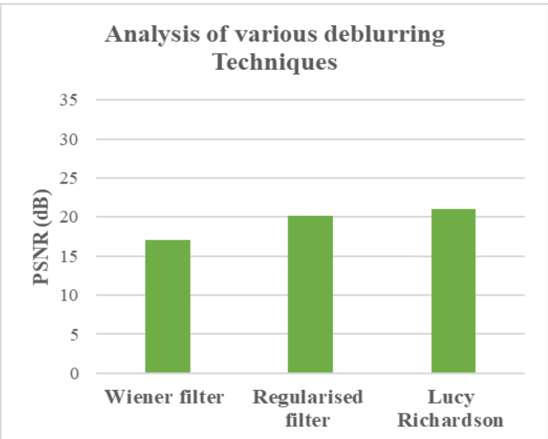

Fig 5a. Charts summarizing the analysis of various non-blind deblurring techniques

PSNR serves as an image quality metric used for quality evaluation of the restored image. Higher the PSNR, better the quality of the restored image. Hence, the PSNR values depicted in Figure 5 indicates further scope for improvement in devising better methods for blind image deblurring. The above analysis justifies the study of the different techniques for blind image deblurring for identifying gaps in literature so that better techniques can be created in the future.

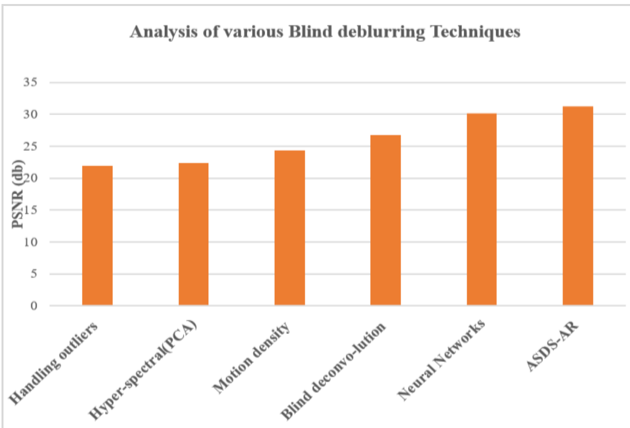

Fig 5b. Charts summarizing the analysis of various blind deblurring techniques

IV. RELATED WORK

About 69 research papers published in reputed journals surveyed for understanding the recent literature on blind image deblurring methods have been categorized as shown in the Fig 6.

Takahashi et. al. (2023) [23], consider blind deconvolution in the Fourier domain. They express the deconvolution problem in the form of quartic term which does not have a Lipschitz continuous gradient. As the convergence analysis of existing first order methods depends on the existence of Lipschitz continuous, traditional first order methods namely the fast

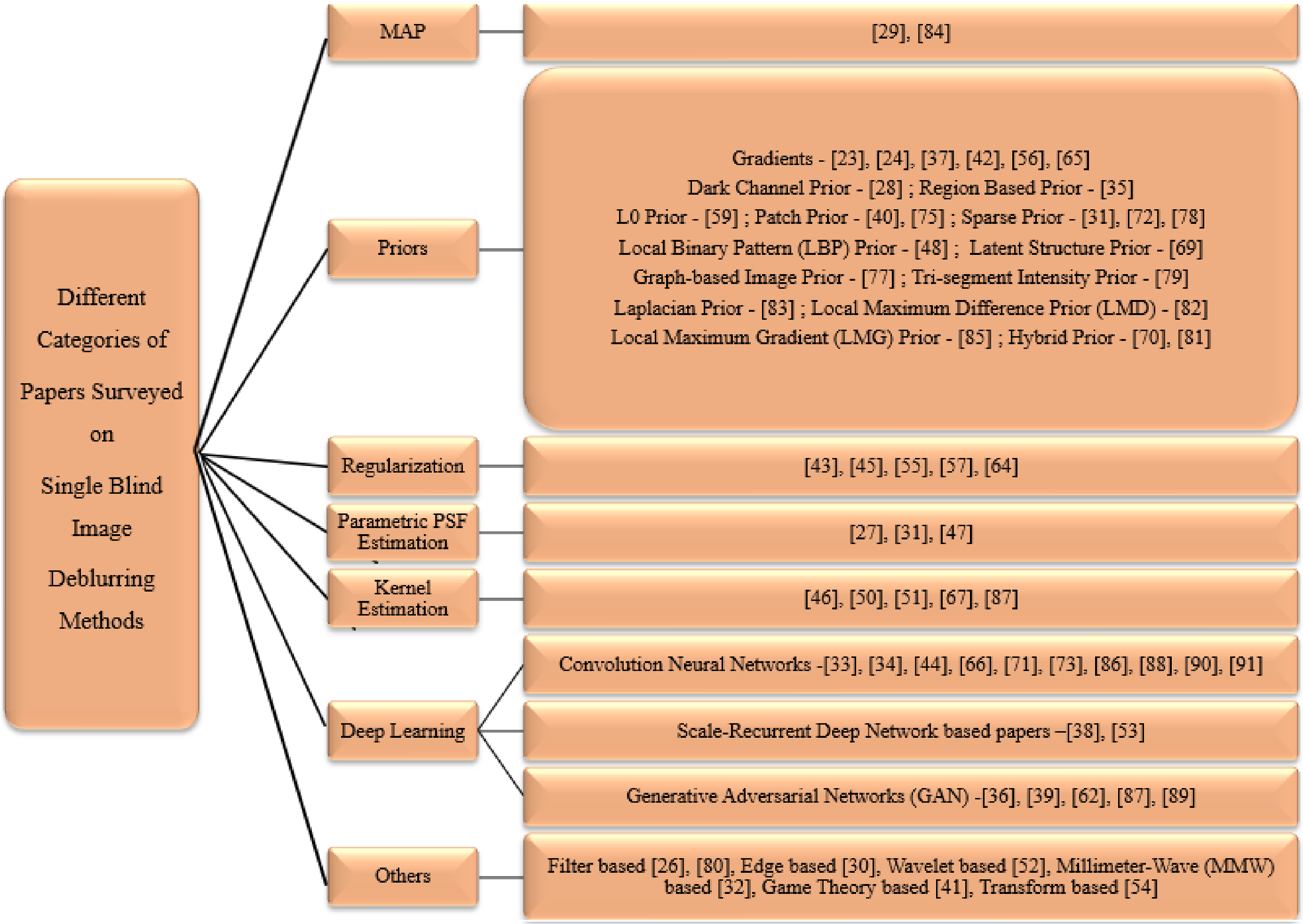

Fig 6. Categorization of papers surveyed on blind image deblurring methods.

A. ***Papers on Maximum a posteriori (MAP)***

Eqtedaei et al. (2022) [29] propose a multiscale blind image deblurring method based on maximum a posterior (MAP) framework focusing on method that has less computational complexity and needs less execution time. K-means clustering is applied on the information about dominant edges of the blurred images are segmented in a coarse to fine scale. Mao et al. (2018) [84] propose a lightweight MAP model for blind image deblurring with necessary constraints on latent image and blur kernel. The authors use an adaptable sparse structure management for MAP inference using an imprecise projected gradient approach.

B. Papers on priors

iterative shrinkage thresholding algorithm (FISTA) are not feasible. The authors propose to use Bregman-based proximal gradient algorithms with extrapolation (BPDCAe) where they demonstrate to have found an appropriate difference of convex (DC) decomposition and kernel generating distance. With the motion blur process, Liu et al. (2022) [24] make use of the property of the patch wise second order gradient (PSG) of an image which happen to be decreasing in terms of its values. The authors propose a model with the PSG to handle the time-consuming trouble of the current prior- based blind image deblurring methods. Initially, sub-sampled of the blurred image at multiple scales is performed then blur kernel estimation and intermediate result are alternately iterated using PSG to get the final blur kernel. Finally, a suitable non-blind approach is adopted to generate the final result. An image prior driven by the dual principles of discriminativeness (DPD) is more crucial and necessary to blind deblurring, according to Shao et al. (2023) [37]. With the notion of DPD, a more concise and intuitive image model reweighted Tikohonov regularization is presented and studied. Particularly, the RTR model is transformed to a discriminative filter and has been harnessed in a plug-and-play framework for blur kernel estimation. Liu et al. (2022) [42] propose a fast-blind image deblurring algorithm which uses the salience map along with gradient cepstrum. The authors take advantage of the recently discovered phenomenon that the extreme values of the salience map of the clear image are sparser than the blurred one, and as a result, they use a L0-regularized salience map prior with the half-quadratic splitting algorithm for optimisation and a gradient cepstrum to prevent too many iterations in each scale and to initialise the blur kernel. The simplified extreme channel prior (SECP) and gradient cepstrum used in Liu et al.'s (2022) [56] fast blind image deblurring algorithm are modelled after and inspired by the clear image's simplified bright channel prior (SBCP) and simplified dark channel prior (SDCP). By imposing the L0 norm constraint on the terms involving SECP and incorporating them into the conventional deblurring framework, the authors optimise the model. An gradient cepstrum is used to determine the initial kernel size and to prevent excessive iterations in each scale. A gradient-based discriminative prior is suggested by Shao et al. (2020) [65] for precise and reliable blur kernel estimation. The authors have used the concept of dual principles of discriminativeness (DPD) for the blind deblurring problem.

Yu et al. (2022) [28] propose a Fractional Order Dark Channel Prior (FODCP) for image deblurring based on the fact that a fractional order calculation can inhibit the noise and preserve the texture information present in the image. The proposed method can produce an efficient dark channel of a degraded image containing blur/noise and can approximate the blur kernel by suppressing the noise in the image. Full-reference & No-Reference metrics are used for assessment of image quality.

Li et al. (2023) [31] propose a joint sparsity prior and multi-scale fusion model for blind text image deblurring, which contains the sparsity priors for estimating latent clean image gradient, blur kernel intensity and high frequency wavelet coefficients of the clear latent image. On the basis of Laplacian weight and saliency weight, the multi-scale fusion technique reduces the influence of the brightness feature of the restored blur kernel. In order to solve the BID problem, Yang et al. (2022) [72] suggest building a novel sparse channel prior derived from the ratio of the dark channel prior (DCP) to the bright channel prior (BCP). The authors use the auxiliary variable technique to incorporate the scant prior data into the iterative restoration process. A blind image deblurring technique based on sparse representation that makes use of the sparsity property of natural images is proposed by Zhang et al. (2011) [78]. It assumes that an over-complete dictionary can be sparsely represent the patches from the natural images. S, Pooja et al. (2022) [35] propose a Region Based Prior Selection (RBPS) model to overcome the presence of ringing, staircase artefacts & loss of information leading to low quality in the deblurred images, which is frequently observed in most of the state-of-the-art image deblurring methods. The authors propose their model is aimed to result in high quality deblurred images without the formation of artefacts by using two algorithms. The First algorithm divides the image into different regions based on the presence of blur so that an appropriate prior can be applied to each region. Then different priors for each image region are applied by using a hybrid regularization algorithm.

Zhang et al. (2022) [48] propose deblurring algorithm for a remote sensing images based on Local Binary Pattern (LBP) prior that prevents over-sharpening by classifying all pixels and processing them in different ways. The authors map the pixels containing the crucial texture features of the images that do not change in the presence of blur using local binary patterns (LBP). The fast-iterative shrinkage-thresholding algorithm (FISTA), the half-quadratic splitting method, and the projected alternating minimization (PAM) algorithm are used to create the mapping matrix.

Li et al. [59] (2021) proposes an edge extraction module based on L0 sparse representation for blind motion deblurring which preserves the edges of images, which are embedded in a multi-scale recurrent network (SRN). Edge enhancement is performed when the current scale transmits information to the next scale. The authors propose an dual-attention mechanism into the encoder-decoder structure which exploits the correlation among pixels and the correlation among channels.

vii. Latent Structure prior: The single-image blind deblurring method proposed by Bai et al. (2020) [69] uses MultiScale Latent Structures (MSLS) to restore sharp images in the coarse scales before using an enhancement process in the fine scale to produce the final deblurred image. By alternately carrying out a sharp image reconstruction with a quick local self-example matching and an accelerated kernel estimation with error correction, the computational complexity is reduced at each scale.

To deal with the task of restoring remote sensing images, Zhu et al. (2022) [40] propose an entirely new prior called the overlapped patches non-linear (OPNL) prior. It is derived from the ratio of extreme pixels affected by blurring in patches where the projected alternating minimization (PAM) algorithm is used along with other techniques like the fast iterative shrinkage-thresholding algorithm (FISTA), fast Fourier transform (FFT), and others. Ljubenović et al. (2017) [75] propose a method called a Gaussian mixture model (GMM) that uses patch-based priors to learn a class adapted prior by training on a dataset of clean images of that class. The authors use a plug-and play approach with a denoiser based on Gaussian mixture model (GMM) and use a weaker prior on the blurring filter.

Bai et al. (2019) [77] propose a graph-based image prior RGTV that promotes a bi-modal weight distribution to reconstruct a skeleton patch from a blurry observation, so that a suitable blur kernel can be simply derived thereafter. The authors design an efficient algorithm to solve the non-convex nondifferentiable optimization problem alternately and suggest the use of accelerated graph spectral filters as a speedup method for blind Gaussian deblurring.

x. Tri-segment intensity prior: Zhang et al. (2020) [79] propose a blind image deblurring method based on the tri-segment intensity prior to estimate a blur kernel from a single motion blurred image. In order to estimate the blur kernel, the sharp image and the blur kernel are alternately estimated. The local minimal solution is significantly avoided in a coarse-to-fine manner using an image pyramid.

Lui et al. (2020) [82] uses the Local Maximum Difference Prior (LMD) for blind image deblurring. The authors adopt the L1 norm constraint to the LMD involved term, compute LMD using a linear operator, and then use a half-quadratic splitting strategy to optimise the method.

Chen et al. (2020) [83] present a blind image deblurring method using on the non-local self-similarity, which can simultaneously capture the intrinsic structure correlation and spatial sparsity of an image. The authors model the structure information of non-local similar patches using the hyper-Laplace prior and insert it into the low rank model.

Chen et al. in (2019) [85] propose a blind deblurring method based on Local Maximum Gradient (LMG) prior. The authors use a linear operator to compute the Local Maximum Gradient, together with an effective optimization scheme.

Cheng et al. (2020) [70] propose a single-image blind deblurring framework called Hybrid Deep Priors Model (HDPM) for kernel estimation and deblurring. The authors propose using an implicit deep prior and hand-crafted explicit prior as regularizations into the MAP inference process to extract the detailed texture and sharp structures of latent image. Li et al. (2018) [81] propose using a data-driven discriminative prior for blind image deblurring. The image prior is suggested by the authors as a deep convolutional neural network (CNN) binary classifier. By incorporating the learned prior into the maximum a posterior (MAP) framework, blind image deblurring is accomplished. The authors use the half-quadratic splitting method and gradient decent algorithm to optimise the deblurring method because the CNN is non-linear.

C. Papers on Regularization

Dong et al. (2022) [43] propose a blind deblurring method specifically for recovering clear Optical coherence tomography (OCT) images from blurred images without a known PSF using spatially adaptive approach. The authors first derive a depth-dependent PSF from the Gaussian beam model then express the blind deconvolution as a regularized energy minimization problem using the least squares method followed by an alternating optimization method. To speed up the execution the authors have used an accelerated alternating optimization method based on the convolution theorem and Fourier transform. Zhang et al. (2022) [45] propose the Gaussian-scale mixture expert field (GSM-FOE) model as a regularised image recovery model which can better fit the higher-order prior of natural images and accurately portray the global prior knowledge of natural images. The authors suggest using IRLS, or iterative reweighted least squares which adaptively changes the parameter values during the iterative process and helps to better maintain the details in the recovered image. Ge et al.'s [55] proposal for a blind image deblurring algorithm makes use of the image surface's Gaussian curvature (GC). By minimising the combined regularization, the authors show that GC regularization, when combined with L0-norm of image gradients, is effective for blind image deblurring while maintaining sharp edges and removing unwanted structures and noises in intermediate latent images. The half-quadratic splitting technique and the Gaussian curvature filter (GCF) are used by the authors to optimise the solution. Duan et al. (2021) [57] attempt to solve blur induced by atmospheric turbulence by proposing suppressed projected alternating minimization (SPAM) a non-blind image deblurring algorithm that uses maximizing L1 regularization (ML1) an convex image prior. The authors' deblurring algorithm employs a soft suppression technique to get rid of the artefacts. Hsieh et al. (2021) [64] propose an effective variational model for blind image deblurring where the authors implement a zero patch minimum constraint for restoring the latent clear image. Important features of the latent image are restored by assigning the patch minimum information from the blurred image back to itself. An adaptive regularizer is used to perform the final image restoration of blurred images having significantly better edge preserving property than the total variation regularizer for image restoration.

D. Papers on Parametric PSF estimation

Nasonov et al. (2022) [27] focus on the estimation of blur parameters. The authors use a patch-based linear approximation to motion blur for estimating the direction of linear blur and a CNN model for estimating the parameters of a linear blur kernel. Li et al. (2023) [31] propose a joint sparsity prior and multi-scale fusion model for blind text image deblurring. The model employs wavelet coefficients with high frequency in the latent clean image, intensity of the blur kernel, and sparsity priors to restore the gradient of the latent clean image. On the basis of Laplacian weight and saliency weight, the multi-scale fusion technique reduces the influence of the brightness feature of the restored blur kernel. Parvaz (2021) [47] presents an algorithm to estimate the point spread function based on framelet transform and $l0-\alpha l1$ norm regularisation for coarse-to-fine iteration. The algorithm uses the framelet transform to improves the restored kernel which is decomposed to the different frequencies and also employs a fraction gradient operator on images with various PSF sizes rather than a regular gradient operator.

E. Papers on Kernel Estimation

Bai et al. (2022) [46] propose a blind single image deblurring called the dual-channel block-cluster deblur algorithm (DCBCD) for specifically restoring space-variant blurred images. The model uses the characteristics offered by the traditional multi image restoration image algorithm and a combines it with those of the single image blind deconvolution restoration algorithm. The authors outline the relative side prior information (RSPI) and kernel estimation using non-dimensional weight-balanced Gaussian measure

(WG-NGM) and propose a clustering-based algorithm is proposed, to restore the space-variant blurred images. Sanghvi et al. (2022) [50] propose an unsupervised & iterative blind deconvolution method for deblurring of low light images. The authors use a deep learning based non-blind Poisson solver to estimate the latent image. The updation of the blur kernel is carried out in an iterative manner where unsupervised loss computed by propagating the gradient of the nonblind solver is backpropogated. Cao et al. (2022) [51] propose three-stage restoration framework for deblurring a single blind image when there is noise in the form of a line pattern. Before estimating an intermediate blur kernel, the authors first eliminate the detrimental effects of the stripe noise in the unidirectional gradient domain, then the missing details of the kernel are rectified using a learning based kernel refinement network and finally, deblurring and noise removal are performed using a non-blind deblurring model based on a low rank decomposition. Zhu et al. (2020) [67] suggest a local rank-based single-image blind deblurring technique. The authors implement adaptive threshold segmentation on a traditional local rank transform to create a blind image deblurring model then a half-quadratic splitting method is used in alternating iterations for the estimation of the blur kernel as well as the deblurred image. To create the desired latent image, a linear combination of the hyper-Laplacian model and the total-variation-l2 model is used. Tian et al. (2021) [87] propose a blind image deblurring method based on dual attention deep image prior (DADIP) network and 2-dimensional (2D) blur kernel estimation with convolutional neural network (CNN). The authors focus on eliminating the ringing artifacts and wrinkles that appear after deburring. The dual attention mechanism is combined with squeeze and excitation network (SENet), which greatly improves the restoration effect of image details while the 2D blur kernel estimation approach via CNN suppresses the ringing artifacts of the image.

F. Deep Learning based papers

Mao et al. (2023) [33] propose a deep idempotent network for efficient single image blind deblurring that uses the idempotent constraint to the deep deblurring network, which improves the non-uniform deblurring performance and achieves stable results w.r.t. re-deblurring multiple times. The authors have designed a deblurring network through progressive residual deblurring with recurrent structure. In order to improve document-image quality by reducing the impact of distortions present in them, Mohsenzadegan et al. (2022) [34] propose a new convolutional neural network (CNN) architecture. The authors use two modules, first for deblurring and the second for jointly denoising and contrast enhancement. A deep variational Bayesian framework (VBDeblurNet) is proposed by Zhao et al. (2022) [44] for the blind deblurring of images, in which deep neural networks can be used to jointly estimate the posterior of the latent clean image and blur kernel. The authors construct the variational distributions parameterized by DNNs to approximate the true posteriors of the latent clear image as well as the blur kernel and learn the network parameters by optimizing the evidence lower bound and then use inference networks to approximate the corresponding posteriors of the clean image and blur kernel in an amortized manner efficiently from an observed blurry image. Bao et al. (2021) [66] propose a method for blind image deblurring and blur kernel estimation. The authors use a convolutional neural network (CNN) with a model-based optimization method to solve the problem of blind image deblurring. A variable splitting technique called half quadratic splitting method (HQS) is used to combine the network model trained by discriminative learning approach with model-based optimization method to restore blind images. Using a hierarchical architecture that is improved from U-Net, Chi et al. (2022) [71] propose the single-image blind deblurring framework Selective Residual M-Net (SRMNet). The multi-scale semantic information is enhanced by the authors using a selective kernel with residual block on the hierarchical structure known as M-Net. In order to recover images from hazy satellite images, Biyouki et al. (2021) [73] propose a kernel mixture structure using the Gaussian kernel as the base kernel, where multiple Gaussian kernels are combined structurally and improved in terms of scales and centres. Nan et al. (2020) [86] propose a framework of variational expected maximization (VEM) to solve noise-blind image deblurring. The authors propose a deep-learning-based computational scheme using a CNN to learn image prior and uses a multi-layer perception network (MLP) to quantify prior uncertainty. Li et al. (2021) [88] propose Multiple Auxiliary Networks (MANet) for single blind image deblurring method which assists norm L1-loss function and enhances the quality of the deblurring image. The main branch of MANet is an encoder-decoder structure made up of residual blocks, and the three auxiliary branches are the edge prediction branch, the multi-scale refinement branch, and the perceptual loss branch. Zhuang et al. (2022) [90] identify issues of SOTA single-instance BID methods and propose a revamped SelfDeblur with a number of crucial modifications to resolve these issues. The authors attempt to address the issue with their model by pointing out that several state-of-the-art (SOTA) single-instance methods are unstable when the kernel size is overspecified and/or the noise level is high. An et al. (2020) [91] propose a blind single image deblurring method Blur Invariant Kernel-Adaptive Network (BIKAnet) that uses a kernel estimation network that produces adaptive blur kernels based on the analysis of the blurred image and a deblurring network that restores sharp images using the estimated blur kernel.

To learn the deblurring from multi-modal medical images, Sharif et al. (2023) [38] propose an end-to-end scale-recurrent deep network combining residual dense block and spatial asymmetric attention (RD-SAM). The residual-dense learning strives to extract salient features, and the spatial-asymmetric block refines the extracted features with local-global attention. A framework for image deblurring that focuses on the reconstruction of high-frequency information is proposed by Liu et al. (2022) [53]. The proposed model implements deblurring processes with high-frequency guidance at various scales simultaneously using a high-frequency reconstruction subnetwork (HFRSN), a high-frequency reconstruction subnetwork (HFRSN), and a multi-scale grid subnetwork (MSGSN). Using a high-frequency information aggregation (HFAG) module and a high-frequency information attention (HFAT) module to direct the feature extraction stage and the feature reconstruction stage in each scale of MSGSN, respectively, the authors also suggest restoring sharpening in images.

Li et al. (2022) [36] propose a dual branch discriminator, which can discriminate image authenticity and distinguish image sparsity simultaneously using a dual-branch GAN which employs various image sparse priors. A new end-to-end generative adversarial network (SDD-GAN) for single-image motion deblurring of remote sensing images is proposed by Zhang et al. in 2022 [39]. The authors propose a Feature Alignment Module (FAFM) and Feature Importance Selection Module (FISM) to successfully recover the texture and details of the blurred remote sensing images. Tomosada et al. (2021) [62] proposes a high quality image deblurring method for large motion blurs called DeblurDCTGAN that preserves texture and suppresses ringing artifacts in the restored image without multi-scale or multi-patch architecture using DCT based loss. The algorithm uses discrete cosine transform (DCT) and requires less computational complexity. Frequency-domain Contrastive Loss Constrained Lightweight CycleGAN, or simply FCL-GAN, is a lightweight and real-time unsupervised BID baseline that Zhao (2021) [87] et al. propose. FCL-GAN is faster and lighter and has no restrictions on the image domain or resolution. To make the model smaller and run more quickly, the authors use the lightweight domain conversion unit (LDCU) and parameter-free frequency-domain contrastive unit (PFCU).

G. Papers from other categories

Lee et. al. (2022) [26] proposes a framework for image restoration improving the quality of the PET image by combining blind deconvolution-based deblurring and noise reduction using a non-local means (NLM) strategy. Almeida et al. (2011) [80] suggest a blind image deblurring method to overcome the drawback of BID methods, which is that iterations must be manually stopped. BID methods do not require prior knowledge of the blurring filter. On the basis of this reasoning, the authors suggest that if the estimation blur filter is effective, the residual will be spectrally white, but if it is not, the deblurred image will contain structured artefacts that are not white.

Hu et al. (2022) [30] in order to deblur blind images, suggest a powerful mixed-order salient edge selection. The authors use zero-order information to retrieve refined structures from the blurred image, then use the second-order information to retrieve the strong structure of salient edges and provide and accurate blurred kernel estimation. Then a combination of three orders is used for blind image deblurring which proves to be a robust salient edge method.

Huang et al. (2022) [52] propose a blind deblurring method called wavelet inspired invertible network (WINNet). This method integrates the wavelet and learning based approaches. The proposed method uses wavelet thresholding, multi-scale forward transform, denoising of the detail coefficients and an inverse transform which is non-linear transform based on the lifting scheme that inherits the sparsifying ability, perfect reconstruction property as well as the multi-scale property of the wavelet transform.

Xu et al. (2022) [32] propose a method called Cycle GAN that can learn the mapping between the blurred Millimeter-Wave (MMW) images and the focused ones without using paired training samples. MMW imaging is used to scan human bodies for concealed weapon detection where the slightest movement introduces blur. The authors investigation of blurring in MMW image due to the shaking of the human body is the first attemp ever to address this problem.

Nasr et al. (2022) [41] proposes to use game theory to solve the problem of blind deconvolution using the the Kalai Smorodinsky solution solved geometrically using the normal boundary intersection (NBI) method.

A transform-based method for estimating the linear motion blur parameters is proposed by Jaravan et al. (2021) [54] based on the extraction of features from the provided single blurred image. To determine the direction of motion blur, the Radon transform of the blurred image's spectrum is used. The length of the motion blur is calculated using the Noise-Immune Discrete Cosine Transform-based (NIDCT) blur metric.

V. OBSERVATIONS

The following observations have been made based on the extensive literature survey done on papers published in recent years presented in section 4 of this paper.

A. Categories of techniques used

Over the years, image deblurring algorithms have made significant breakthroughs leading to the development of a number of methods and categories of methods. Classification of image deblurring techniques are summarized in Table 2.

Table 2: Classification of Image Deblurring Techniques

Classification Criteria	Categories of techniques
Based on knowledge of the blur kernel	Blind deblurring, non-blind deblurring
Based on image input	Single frame, multi frame
Based on degradation type	Motion blur, gaussian blur, defocus blur, turbulence blur, etc.
Based on method of deblurring algorithm	Optimization-based deblurring method and deep learning deblurring method
Based on consistency of degradation	Space-changing blur and space-invariant blur

B. Image Quality Metrics used

Considering the increasing applications of image processing, enhancement & restoration there is a lot of research being done in the computational Image Quality Assessment (IQA) methods. Researchers use different Image Quality Metrics (IQM) to assess the quality of output images produced by their model. The many image quality metrics can be categorized into two broad categories – subjective & objective are summarized in Figure 7. In subjective IQM's, the given image(s) is evaluated by human observers through subjective evaluation by assigning scores to them and hence quantifying the visual quality of an image. These methods are time consuming hence inconvenient for real life implementation and cannot be integrated with automated tools. In objective IQM's the main purpose is to use mathematical models to automatically and accurately evaluate the quality of an image. Objective IQMs can be grouped according to the concept of reference image or use of Human Visual System (HSV) models. Based on the concept of a reference image objective IQMs can be subcategorized into three classes: Fully-Reference (FR), Reduced-Reference (RR) and No-Reference (NR). FR IQM's evaluate the quality of a pair of images containing the ground-truth and the distorted images.

Some of the FR IQMs are Mean Square Error (MSE), Mean absolute Difference (MD), Pearson Correlation Coefficient (PCC), Spearman Rank Correlation Coefficient (SRCC), Peak signal-to-noise-ratio (PSNR). Reduced-reference IQMs assess the quality of images which have the distorted images and some additional information about the original ground truth image. NR IQM's assess the quality of images which only have the distorted image without any other prior information of how the free-distortions image should look like. Some of the NR IQM's are Blind / Reference Less Image Spatial Quality Evaluator (BRISQUE), Perception based Image Quality Evaluator (PIQE), Natural Image Quality Evaluator (NIQE), Blind Image Integrity Notator using DCT Statistics (BLIINDS), Distortion Identification Based on Image Identification and Integrity Test (DIIVINE). The constraints on size of the paper restrict the detailed description of these metrics as well as numerous other IQM's in the literatutre.

C. Benchmark Datasets

Several datasets have been used by researchers for evaluating the performance of deblurring algorithms. Most researchers have used existing datasets which are specific to a certain domain like medical imaging, remote sensing, facial images, textual images, etc which originally do not contain blur and hence introduce blur/noise to a clean image and evaluate the performance of their algorithms on the distorted image. Benchmark datasets specifically created for evaluating the performance of deblurring algorithms are summarized in Table 3.

D. State-of-the-art & benchmark deblurring algorithms

Fergus et al. (2006) [92] propose a technique for removing the effects of unknown camera shake from an image. The authors use natural image priors and advanced statistical techniques focused on kernel estimation. The results however indicate presence of ringing artifacts. Shan et al. (2008) [110] propose a technique for single image motion deblurring by first exploring the major causes of visual artifacts and then apply advanced iterative optimization that, until convergence, alternates between blur kernel enhancement and image restoration. The proposed method is a probabilistic model that unifies blind and non-blind deconvolutions into a single MAP formulation. Cho & Lee (2009) [93] propose a fast deblurring method which works with image derivatives rather than pixels to accelerate the iterative deblurring process, both latent image estimation and kernel estimation. Xu & Jia (2010) [96] propose a motion deblurring method which adaptively select useful edges for kernel estimation and uses the iterative support detection (ISD) based kernel refinement with adaptive regularization to improves the result quality. Whyte et al. (2010) [102] propose a deblurring method which is a parametrized geometrically consistent model of non-uniform image blur. Krishnan et al. (2011) [98] propose a fast blind deblurring method which uses a new type of non-convex image regularization which favours sharp images over blurry ones and provides the sharpest image at the lowest cost. The ratio of the l1 norm to the l2 norm on an image's high frequencies is the suggested regularisation function. Levin et al. (2011) [100] propose an algorithm which optimizes the MAP algorithm and performs alternating minimization to solve for the original sharp image and the true blur kernel. Hirsh et al. (2011) [109] present a blind deblurring algorithm on single image for removing motion blur of non-uniform nature induced by camera shake and uses Efficient Filter Flow (EFF) & Projective Motion Path Blur models (PMPB models) to achieve the results. A generalised and sound mathematical L0 sparse expression is used in Xu's (2013) motion deblurring

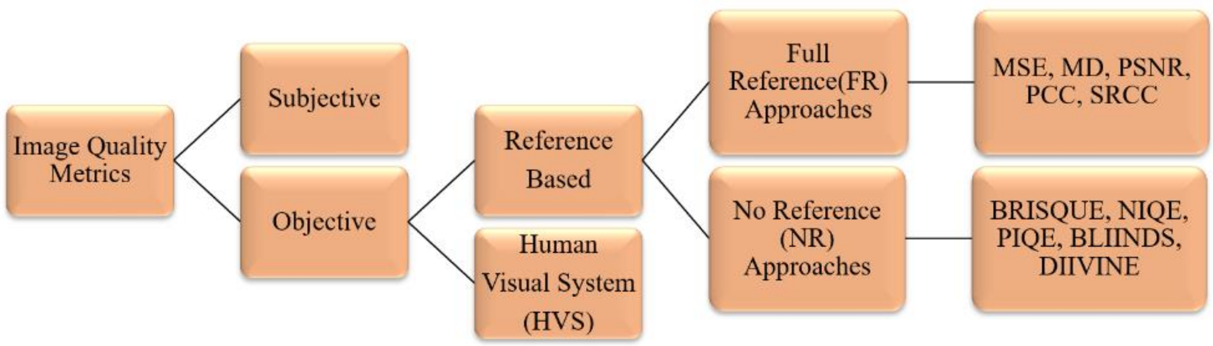

Figure 7: Classification of Image Quality Metrics (IQM's)

Table 3. Benchmark Datasets for evaluating the performance of deblurring algorithms

Author	Synthetic/ Real	Blur Model	Latent Images	Kernels/ Trajectories	Blurred Images
Levin et al. [119]	Synthetic	Uniform	4	8	32
Kohler et al. [120]	Real	Non-Uniform	4	12	48
Lai et al. [121]	Synthetic	Uniform & Non-Uniform	25	4	200
Pan et al. [122]	Synthetic	Uniform & Non-Uniform	60	8	480
Sun et al. [104]	Synthetic	Uniform	80	8	640
Nah et al. [111]	Synthetic	Uniform & Non-Uniform	3214	1	3214
Rim et al. [123]	Synthetic	Uniform & Non-Uniform	232	-	4556

method. Xhang (2013) [95] propose a multi-image blind deblurring method which uses a penalty function that combines the latent sharp image, blur kernels, and noise variances. By applying a series of directional filters to the input image, Zhong (2013) [97] propose a new method for dealing with noise in blind image deblurring. This method uses the inverse Radon transform to reconstruct the blur kernel and estimates an accurate Radon transform of the blur kernel from each filtered image. Sun et al. (2013) [104] propose a kernel estimation method which uses an edge-based approach using patch priors on edges of the latent image. The authors also propose a new synthetic test set of 640 high-resolution natural images of diverse scenes. Michaeli & Irani (2014) [99] propose a blind-deblurring method based on the internal patch recurrence property within a single natural image used as a cue for estimation of the blur kernel. Pan et al. (2014) [101] propose exemplar-based method for deblurring face images which exploits the structural information. kernel estimation is done using face structure and reliable edges from exemplars. Total variation is used by Perrone et al. [103] to analyse the application of sparse gradient priors. The authors confirm that the problem formulation of total variation blind deconvolution as a maximum a priori in both sharp image and blur is prone to local minima. The dark channel of the recovered image is minimised using a L0-regularization term in Pan et al.'s (2016) [105] proposal for a straightforward and efficient blind image deblurring method based on the dark channel prior. For text image deblurring, Pan et al. (2016) [106] suggest an efficient L0-regularized prior based on intensity and gradient. The authors construct a 120-image dataset containing 15 ground truth document images and 8 kernels. Yan et al. (2016) [107] propose a joint prior by combining Bright and Dark Channel Prior called extreme channels prior (ECP). Nah et al.'s (2017) [111] non-uniform blind deblurring method directly restores latent images without relying on any constrained blur kernel model, and it employs a multi-scale convolutional neural network. The proposed model follows a coarse-to-fine approach and is trained in multi-scale space. The authors construct a dataset is composed of 3214 pairs of blurry and sharp images at 1280x720 resolution. Kupyn et al. (2016) [112] propose DeblurGAN for blind motion deblurring based on a conditional GAN and optimized using a multi-component loss function. Tao et al. (2018) [113] present a coarse-to-fine blind image deblurring technique called Scale-recurrent Network (SRN-DeblurNet). Chen et al. in (2019) [85] propose a blind deblurring method based on Local Maximum Gradient (LMG) prior. The authors use a linear operator to compute the Local Maximum Gradient, together with an effective optimization scheme. Zhou et al. (2019) [114] propose a stereo image deblurring method with Depth Awareness and View Aggregation network (DAVANet). The authors combine the estimation of bidirectional disparities with deblurring using a fusion network. The authors have created and shared a dataset for the purpose of stereo deblurring which contains20,637 blurry & sharp stereo image pairs along with their bidirectional disparities. Kupyn et al. (2019) [99] propose DeblurGAN-v2, an improvement over DeblurGAN [112] for single image motion deblurring. Gao et al. (2019) [100] propose a method for dynamic scene deblurring using feature transformation modules with nested skip connection structures. The authors analyze the principles of effectively using parameters in deblurring CNNs and propose a parameter selective sharing scheme in contrast to parameter independence and sharing schemes. Ye et al. (2019) [102] propose a method for blind image deblurring called scale-iterative upscaling network (SIUN). It uses weights sharing across iterations. Wen et al. (2020) [92] suggests patch-wise minimal pixels (PMP), a sparsity prior of local minimal pixels having the property that a clear image with more sparsity will have a larger PMP of than that of blurred image and so can be used to differentiate between clear and blurred images. In Qi et al.'s (2020) [101] proposal, we use a dense feature fusion block made up of channel attention and pixel attention modules to propose a blind image deblurring method. The authors employ scale attention modules and densely connected multiple dense feature fusion blocks to acquire high-order feature representation.

E. Publication Statistics

This section presents the bifurcation of surveyed papers according to publisher & year of publication and is presented in Figure 8.

V. CONCLUSIONS

This paper is based on a survey of 69 research papers in last 5 years. The survey is constrained by the availability of quality research papers. Categorization of the different

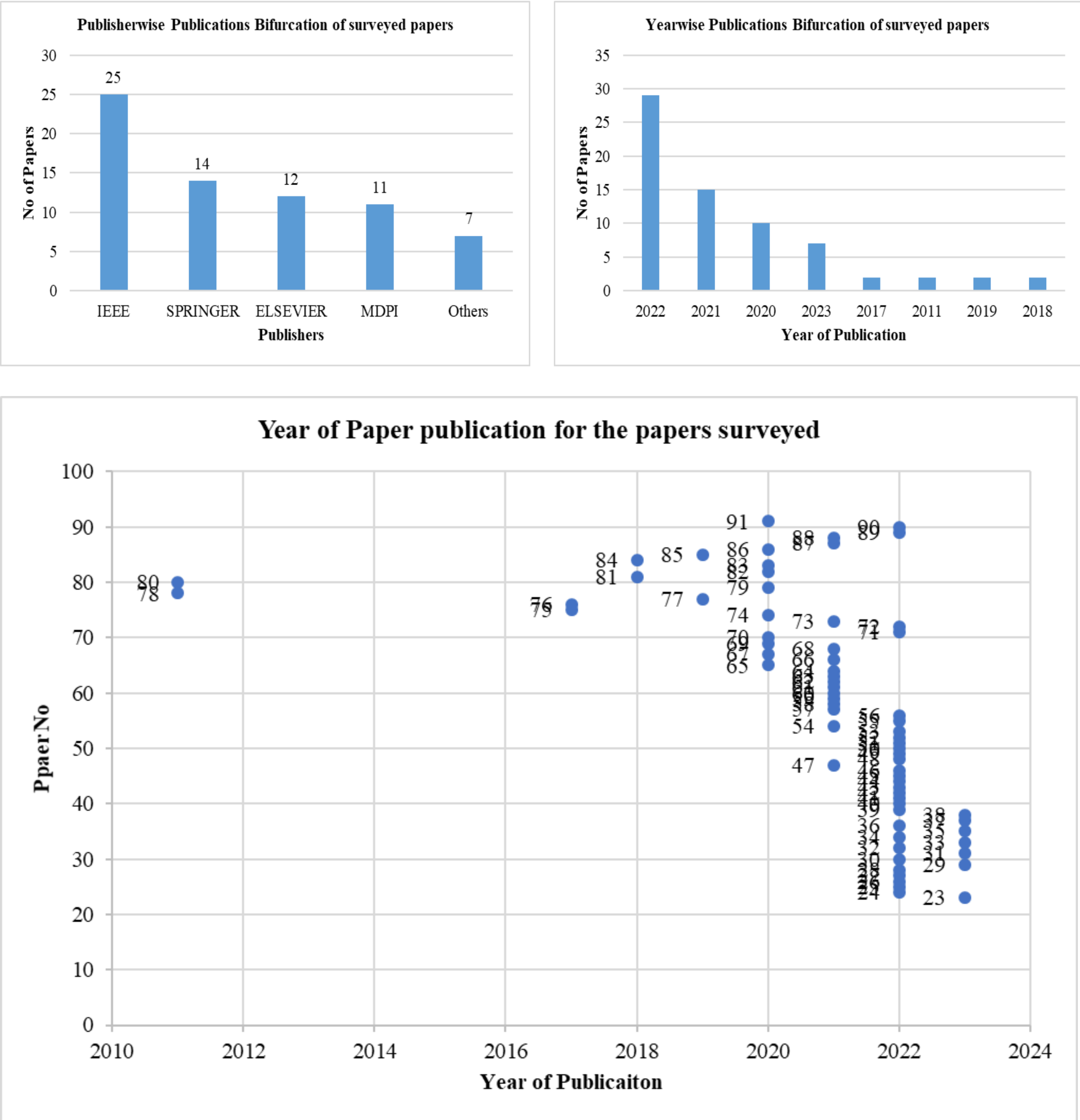

Figure 8: Bifurcation of surveyed papers according to publisher & year of publication

deblurring algorithms according to possible criteria is presented in Table 2, categorization of frequent (not all) Image Quality Metrics (IQM's) is presented in Figure 7. Frequently used benchmark datasets for evaluating the performance of deblurring algorithms is presented in Table 3. A short review of state-of-the-art & benchmark deblurring algorithms used for comparative quantitative analysis is presented in section 5D. We conclude by stating that considerable work has been done in the domain of image deblurring and that the use of blind image deblurring methods are justified for enhancement of single blurred images where original reference image is not available.

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