Heliyon 9 (2023) e17332

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

A state-of-the-art review of image motion deblurring techniques in precision agriculture

Yu Huihui [a,b,c], Li Daoliang [b,c,d,e], Chen Yingyi [b,c,d,e,*]

[a] School of Information Science & Technology, Beijing Forestry University, Beijing, 100083, PR China
[b] National Innovation Center for Digital Fishery, Beijing, 100083, PR China
[c] Key Laboratory of Smart Farming Technologies for Aquatic Animal and Livestock, Ministry of Agriculture and Rural Affairs, Beijing, 100083, PR China
[d] Beijing Engineering and Technology Research Center for Internet of Things in Agriculture, Beijing, 100083, PR China
[e] College of Information and Electrical Engineering, China Agricultural University, Beijing, 100083, PR China

A R T I C L E I N F O

Keywords:
Precision agriculture
Motion blurred image
Motion deblurring
Blur kernel
Deep learning

A B S T R A C T

Image motion deblurring is a crucial technology in computer vision that has gained significant attention attracted by its outstanding ability for accurate acquisition of motion image information, processing and intelligent decision making, etc. Motion blur has recently been considered as one of the major challenges for applications of computer vision in precision agriculture. Motion blurred images seriously affect the accuracy of information acquisition in precision agriculture scene image such as testing, tracking, and behavior analysis of animals, recognition of plant phenotype, critical characteristics of pests and diseases, etc. On the other hand, the fast motion and irregular deformation of agriculture livings, and motion of image capture device all introduce great challenges for image motion deblurring. Hence, the demand of more efficient image motion deblurring method is rapidly increasing and developing in the applications with dynamic scene. Up till now, some studies have been carried out to address this challenge, e.g., spatial motion blur, multi-scale blur and other types of blur. This paper starts with categorization of causes of image blur in precision agriculture. Then, it gives detail introduction of general-purpose motion deblurring methods and their the strengthen and weakness. Furthermore, these methods are compared for the specific applications in precision agriculture e.g., detection and tracking of livestock animal, harvest sorting and grading, and plant disease detection and phenotyping identification etc. Finally, future research directions are discussed to push forward the research and application of advancing in precision agriculture image motion deblurring field.

1. Introduction

Computer vision, image processing and deep learning technology have grown rapidly and applied widely in agriculture, due to low cost of equipment, high computation power of computer and ability of non-destructive assessment [1,2]. While in practice agricultural producing, the scene of image shooting is roughly complex, e.g., fast movement of animal, device shaking, nature environment influence and other relative motion. These extrinsic factors always cause motion blurred image and roughly affect applications of agriculture images [3]. Significantly, agricultural living things are not like inanimate objects, as animal motion or shape

* Corresponding author. China Agricultural University, 17 Tsinghua East Road, Beijing, 100083, PR China.
E-mail address: chenyingyi@cau.edu.cn (C. Yingyi).

https://doi.org/10.1016/j.heliyon.2023.e17332
Received 25 December 2022; Received in revised form 7 June 2023; Accepted 14 June 2023
Available online 19 June 2023

transformation further adding the image blurry degree. For instance, fish swimming and deformation of fish body blurs add complexity to fish tracking and trajectory analysis [4]. Pig movement and deformation blurs make the precision biomass estimation more difficult [5]. Current techniques mostly adopts increasing the shutter speed of camera to get clear pictures, which still cannot solve the effects of motion blur completely in practice agriculture production. Hence, it is still a significant demand to explore the image motion deblurring techniques for images deblurring of complex and dynamic agriculture scene in precision agriculture.

Image motion deblurring has grown extensively as critical and imperative technology for motion blurred image reconstruction [6]. It is possible mathematically to reconstruct the underlying image from non-ideal image, that blurred by extrinsic moving factors. so that information present but hidden in the data is revealed with less motion blur. While, image deblurring is an ill-posed problem in image processing, since too many parameters are unknown for a deblurring algorithm [7]. Moreover, the real dynamic agriculture scene and targets characteristics result in image and video always suffering from spatially varying blurs from various sources [8]. The motion of livestock animals, body deformation and rotation of plant leaves bring out occlusion, overlap, multi-scales, and blur edge expand, which result further loss of blur semantic information and local feature loss. Thus, it is difficult to parameterize the pixel-wise varying blur kernel in agriculture dynamic scene with simple homography and estimation of blur kernel or blur edge. The agriculture scene image motion deblurring has been a more challenging task for image deblurring. Fig. 1 gives an over-understanding for computer vision and image motion deblurring techniques application in agriculture, from technology, application, reasons for motion blur, difficulties and method.

Over the years, numerous techniques of image deblurring have been proposed to tackle non-blind or blind deblurring problems, that classic and well-known classification schemes are employed [9]. The motion blur kernel, also known as one kind of point spread function (PSF) is core discussed content [10]. For non-blind deconvolution, the blur kernel is assumed to be known and used to estimate the sharp image. By contrast, the blind deblurring problem is more ill-posed, that means the blur kernel is unknown. Therefore, the task of blind deblurring becomes the estimation of the sharp image and the blur kernel from the degrade image. Traditional methods of motion deblurring include the Richardson-Lucy method, Wiener filter method and Markov random field method [11]. While, for agriculture image processing, the deblurring methods are preferred to blind deblurring, because of the changing scenes of agriculture, changes of irregular morphological and unpredictable external factors. In recent years, the deep learning algorithm as a novel blind deblurring technology has been presented for motion image deblurring [12], because of its robust feature representation abilities. It surpasses previous feature representation methods based on manual design in portraying the superiority of image features. It is found that deep learning methods are most widely used in precision agriculture image motion deblurring through section 4 literature reviews.

background in agriculture.

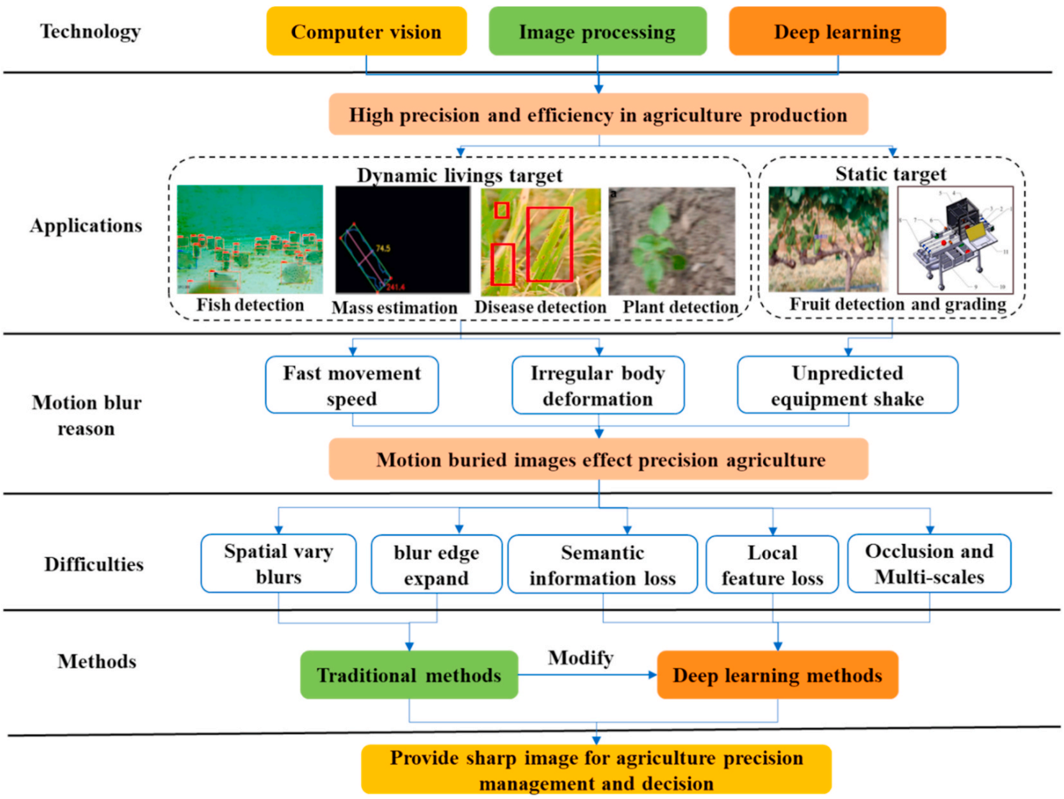

Fig. 1. Computer vision and motion deblurring technology application.

Image motion deblurring has opened a new avenue for the development of computer vision attacked by its unique advantages. It has been widely studied and applied to many fields. The application of image motion deblurring in precision agriculture can yield benefits in terms of productivity and efficiency. However, the depth and scope of its application in agriculture are initial stages. The cutting-edge motion deblurring algorithms are still not mature and limited. Hence, one of objects of this study is to summarize the application of image motion deblurring technology in precision agriculture in the past decade, including precision fertilizer spreading, precision livestock farming, precision weed detection, intelligent postharvest sorting and grading and plant precision detection and phenotyping identification, etc. In addition, we briefly introduce the image motion deblurring methods and analyze the advantage and disadvantage of each type technique. We also discuss the challenge for precision agriculture image motion deblurring and the future directions of research in image fusion technology. This paper provides the current status of application of image motion deblurring technology in precision agriculture and valuable guidance for further developments, which can solve practical application problems and bring a significant breakthrough in intelligent and precision agriculture.

2. Motion blurred image categories in precision agriculture

With the rapid development of computer vision technology in recent year, image processing methods are utilized in many agriculture fields, such as livestock detection and monitoring [13], identification of plant phenotyping and disease diagnose [14], fruit sorting and grading and mechanized fertilization [15]. These fields are the high standard for image quality in agriculture precision applications. While, in the agriculture nature environment, the images are usually degraded due to the fast movement of livestock or shake of image capture device [4]. According to the different scenes, the motion blurred image can be divided into the following categories, shown in Fig. 2.

(1) Camera static and object motion blurred image: This type blurred image is the most common blurry image in agriculture. It can usually be divided into blurred images of animal motion and blurred images of plant phenotyping. In precision agriculture, detection, monitoring and behavior analysis of animal have become increasingly crucial for animal welfare breeding and are important ways to increase production. While fast movement of animal always results in motion blur, which leads to false detection or other failed analysis [16]. The environment may cause motion blur images for the extraction of plant phenotyping, which add the difficulty for diseases detection [17]. These motion blurred images are irregular and the motion blurs are non-uniform. The targets are usually large-scale. Thus, the relatively large scale targets with large area non-uniform blurred parts are roughly difficult for image preprocess tasks.

(2) Camera motion and object static blurred image: This type motion blurred image is another common blurred image in

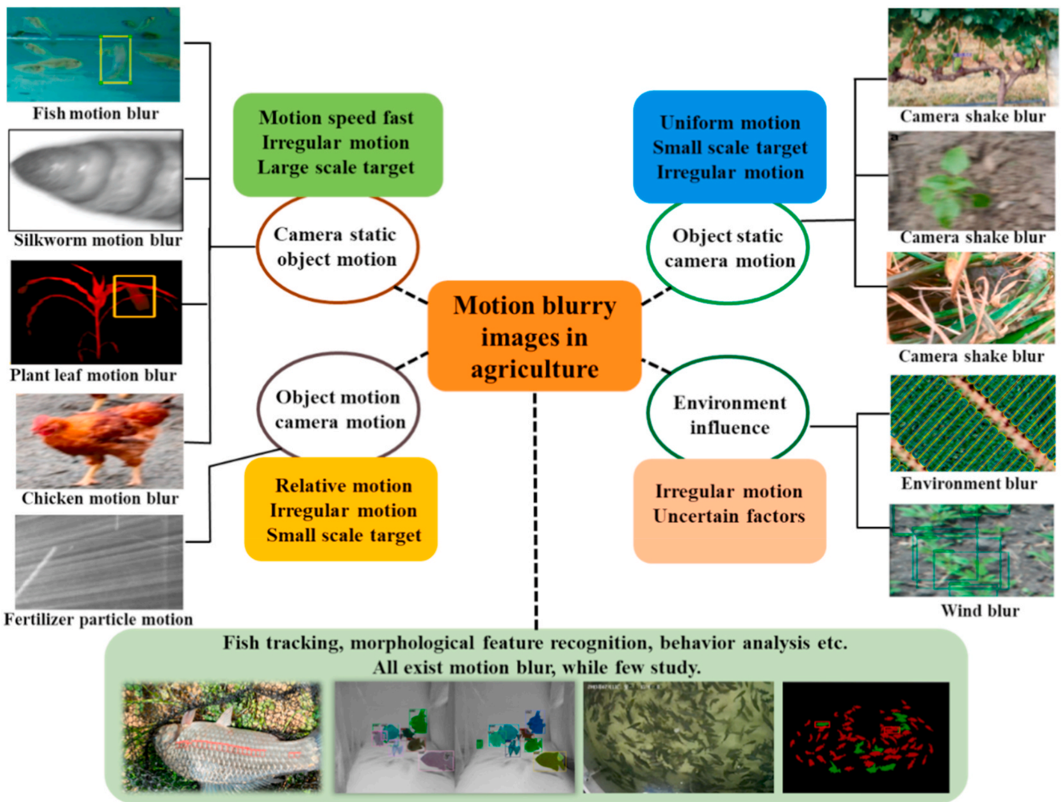

Fig. 2. Motion blurred image categories in agriculture application.

precision agriculture. It usually appears in weed detection or harvest fruit detection [18]. In these agriculture scenes, the camera is usually installed on a movement equipment to capture the image of static plants. So, this kind of image capture way always easily results in motion blurred images and affects the application in precision agriculture. For this type blurry image, the blurry area is large and the blur kernels are uniform [19]. For these images, the detection objects are relatively small scale targets.

(3) Camera motion and object motion blurred image： Camera motion blurred images usually involve moving objects. Such as fertilizer spreading in agriculture, there are always wind and other factors adding the blurry effect for the capture image [20]. In fertilizer spreading process, the device motion and fertilizer particle motion both result in the motion blur.

(4) Agriculture environment influence: In addition to the above factors of blurriness, there is some uncertain factor for high altitude camera, such as the unmanned aerial vehicle (UAV) system [21]. There are uncertain factors for this big scene, such as camera shake, big wind and fast speed etc. For this motion blurred image, the blur kernel is spatial variation and un-uniform, which makes the image deblurring more challenging.

3. Development of image motion deblurring techniques

The image blurring process can be named as image degradation process. In 1972, Richardson presented the image degradation model [22]. In practice agriculture production, the complex environment and motion of animal, plant, and device always result in motion blurring images and roughly affect the effective application of computer vision in precision agriculture [23]. Thus, motion deblurring is a fundamental and cutting-edge problem in the computer vision field. In the past two decades, motion deblurring techniques have been carried out to help develop better models and algorithms for the precision understanding of agriculture images. In agriculture, image deblurring technology has been applied in some special areas but is still immature. In this part, we summarize the typical image motion deblurring techniques development from basic motion deblurring algorithms, traditional motion deblurring methods and neural network-based deep learning deblurring methods.

3.1. Motion blurring algorithm

(1) Blur kernel.

The blur kernel, also known as the point spread function (PSF) caused an image pixel to record light photons from multiple scene points [24]. Many factors can extrinsically or intrinsically cause image blur. For image motion deblurring, the blur is mainly divided into object motion blur and camera shake blur. These blurs can degrade an image or video in different ways. An accurate estimation of the sharp image and the blur kernel requires an appropriate modeling of the digital image formation process modeling. The image formation model can be formulated as follow Eq. (1) [11]:

$$y = S(f(D(P(s) * h_{ex}) * h_{in})) + n \tag{1}$$

This formula represents a typical camera system image formation that encompasses the radiometric processes by which a 3D world scene is projected into a 2D focal plane. The photography process can be modeled as a concatenation of the perspective projection and the geometric distortion. The final digital image is formed by discretization duo to the nonlinear sensor response. In Eq. (1), y is the observed image, s is the real planar scene, $P(\cdot)$ and $D(\cdot)$ are the perspective projection and geometric distortion operator, $f(\cdot)$ denotes the nonlinear camera response function. h_{ex} is the extrinsic blur kernels caused by external factors such as motion blur. h_{in} denotes the blur kernels determined by intrinsic factors such as defocus blur. The S is the discretization process, and * denotes the mathematical convolution operator. n is the additional noise.

For image motion deblurring, it is interested in recovering a sharp image with no blur effect, rather than the geometry of the real scene. Hence, focusing on the image plane and ignoring the sample errors, the image deblurring formulation can be described as Eq. (2) [11]:

$$y \approx f(x * h) + n \tag{2}$$

Where x is the latest sharp image, it is obtained from $D(P(s)$ and h is the blur kernel for image deblurring, approximately introduced by h_{ex} and h_{in}, and assumed by most approaches. The f camera response function will still significantly influence the deblurring process if it is not appropriately addressed. However, in many researches, the f is neglected or as a preprocessing step for simplification in deblurring method. And then obtain a further simplified formulation, which is introduced most commonly in research as Eq. (3) [11]:

$$y = x * h + n \tag{3}$$

We can introduce the non-blind and blind deblurring methods from the above formulation. For non-blind deblurring methods, it is to recover a sharp image x by observation y and given blur kernel h. Blind deblurring methods are to recover a sharp image x and h, usually are obtained by iterative learning. This survey mainly focuses on the motion blur kernel and the noise n. Next, we will introduce two causes of motion blur kernel and types of the motion blur kernel.

(2) Motion blur.

For image motion deblurring, the blurred image is mainly caused by object motion blur and the camera motion blur. Object motion blur is caused by the relative motion between an object in the scene and the camera system during exposure time [25]. Suppose the motion is very fast relative to the exposure period. In that case, we may approximate the resultant blur kernel as a linear blur, which can be described as follow formulation as 1D local average of neighboring pixels and given as Eq. (4):

$$h(i,j,L,\theta) = \begin{cases} \frac{1}{L}, if \sqrt{i^2 + j^2} \leq \frac{L}{2} and \frac{i}{j} = -\tan\theta \\ 0, others \end{cases} \tag{4}$$

The (i,j) is the coordinate originating from the center h. L represents the moving distance and direction. Fig. 3a gives simulated example of a Lena standard test image corrupted by 30°-directional motion. Whereas in the case of object motion, only the moving object image is blurred linear, that blur kernel is regarded as uniform blurring blur [26,27]. Real motions are extremely complex in agriculture, because of the large space of possible motion paths. Such a simple parametric model cannot approximate them. For example, in Fig. 3b, the camera and the cattle are both moving, which results in the motion blurred image and increases the difficulty for the target identification. It cannot use a uniform blur kernel to process the whole image in this case. We will introduce another un-uniform motion blur. This type of blur also usually occurs in the camera motion blur.

Camera shake blur is another kind of motion blur, caused by camera motion during exposure in handled photography or in low-light situations. In an ideal scene, the camera is only translated and the resultant blur is approximately spatially invariant [7]. It can be modeled as the simple object linear motion blur as in Eq. (4). However, the camera rotation motion blur is more complex, especially for unmanned aerial vehicle (UAV) loaded camera will cause an irregular direction when photographing [21]. For this motion blur image, it is assumed that the entire image is uniformly blurred and the blur kernel remains unchanged. The corresponding restoration method is called spatially invariant motion blur [7,28,29].

3.2. Traditional motion deblurring techniques

Image motion deblurring is categorized into two main categories, traditional deblurring techniques and deep learning deblurring techniques. The subsequent section contains the details of existing well-known deblurring techniques for motion-blurred images, along with their strengths and weakness. The earliest and typical methods for image deblurring are based on the Bayesian algorithm. The well-known methods include the Richardson-Lucy algorithm (RL) [30], Wiener filter [31], Edge prediction, variational Bayesian methods, etc. These methods are identified as a non-blind or blind deblurring method, according to whether the blur kernel is known or unknown.

(1) Richardson-Lucy method

The R-L algorithm uses the maximum likelihood method to repair blurred images and succeeds in many motion deblurring processes. Several improved R-L algorithms were used for image motion deblurring. For example, Yong et al. addressed an improved R-L algorithm [32]. This method combined the local prior to suppress the ringing artifacts caused by failures in the blur kernel estimation. Yang et al. proposed an a unified framework called the Gradient Attentuation Richardson-Lucy algorithm, which is applied to solve the loss of image details due to the suppression of the ringing artifacts around the region with strong edges [33]. Shah et al. also modified the Richardson-Lucy algorithm with weight calculation based on graph-cut to obtain good estimates of the unblurred image with ringing reduction. The method involves the selection of different weights for edges and smooth regions such that the ringing effect over R-L iterations can be reduced [34]. The above methods all used the Richardson-Lucy algorithm to solve the ringing artifacts for the non-blind motion deblurring. The R-L algorithm is also extended to incorporate a depth-aware motion blur to solve the spatially-varying point-spread functions in real world obtained image [6].

(2) Wiener filter method

The Wiener filtering method uses the minimum equalization criterion achieve the purpose of image deblurring. The Wiener filter algorithm has greatly ability to reduce the blurred image noise. It is usually used in a generating phase-inverting grids method to help


(a) Simulation linear blur (b) Real motion

Fig. 3. Simulation linear motion blur images and real agriculture motion blurred image.

reduce the noise for optical image deblurring [35,36]. Wiener filter algorithm is also used to restore object image of different sizes, or used to design a simple motion deblurring model to promote the deblurring speed [37]. Moreover, these models have been applied to synthetic and real-world images, such as image of rotational movement and photoelectric image [38–41]. In recent years, the Wiener filter algorithm has been combined with the deconvolution algorithm for non-blind image motion deblurring, which effectively improve the model performance [42,43]. Summarize above approaches, the Wiener filtering algorithm is suitable to design the model, which needs to reduce the noise and solve the spatial deblurring blur estimation.

(3) Markov random field method

The principle of the Markov random field (MRF) algorithm uses the grid structure to express the spatial relationship in the image. Woo et al. built preprocessing step that include registration and intensity matching and a data combination approach with the edge-preserving property. This method is carried out by Markov random field optimization, which is a super-resolution reconstruction technique based on volumetric tongue MR images acquired from three orthogonal acquisitions [44]. Moreover, Abbadi et al. also proposed a filter method based on combining Markov basis and Laplace filter. It is slightly modified to make it appropriate for color images and solved the escalation image edge content [45]. A framework of Markov Random Field (MRF) was formulated to solve for the depth map by exploiting both stereo cues and motion blur cues. This method solves that the scene depth variation is an important factor that leads to spatially-varying camera motion blur [46]. It is challenging to find distinct features to learn the extent of motion blur through deep learning precisionly. The Markov random field model was used to infer a dense non-uniform motion blur field enforcing motion smoothness in deep learning motion deblurring models [47,48].

(4) Variational Bayesian method

The Variational Bayesian (VB) method estimates the approximate joint posterior probability distribution of the blur kernel and the implicitly clear image. It integrates all possible hidden clear images to calculate the marginal probability distribution of the fuzzy kernel. So that the k with the largest marginal distribution is the estimated fuzzy kernel [49,50]. Wipf and Zhang addressed that the VB method can be considered as an unconventional Maximum a Posteriori method when it uses a specific form of a prior that implicitly combines clear images, blur kernels and noise levels [51]. Although compared with earlier methods based on Maximum a Posteriori, this type of method is less likely to converge to non-trivial solutions, but requires extremely complex mathematical derivation and high computational complexity. Thus, the variational Bayes method is used for ringing effects removal [52], and adaptive edge selection [53] for blind motion deblurring, achieved better results.

4. Edge prediction method

Edge prediction method still involves the iterative estimation process of the implicitly clear image and blur kernel, so it is considered as a variant of the Maximum a Posteriori based method. The method is based on explicit edge prediction and uses the combination of a simple bilateral filter and an impulsive filter for the estimation of the blur kernel. It performs detail suppression, edge enhancement of intermediate deblurred image, and the processing of the processed image [54,55]. The intermediate deblurred image can be estimated using simple Gaussian gradient priors by using the explicit edge prediction, which greatly improves the running speed of the algorithm [56,57]. This type method lacks effective modeling of the formation process for motion blur and the actual deblurring performance is poor.

At the end of this section, we summarize the traditional image motion deblurring techniques in Table 1. These methods can solve the ringing affect, noise and blurry edge estimation for the motion blurred image. They are relatively simple and commonly employed for image preprocessing to enhance image quality. Table 1 presents detailed information on the name, basic theory, advantages, and disadvantages of each technique. We analyze the results of the motion deblurring techniques using a deblurring ability metric, where a greater number of stars indicates improved motion image deblurring capabilities.

However, these methods have limitations, including the need to obtain the blur kernel and the fact that restoration results are often not ideal. These techniques may also result in the loss of deep image information and an inability to fully capitalize on the relationships between image frames and pixels. Despite these shortcomings, these methods can still be employed during the image preprocessing stage for computer vision methods, providing higher quality image datasets.

4.1. Neural network based motion deblurring techniques

The nature of the blur kernel is to cut off a high-frequency band of image, and it is not easy to recover the high-frequency information. Deep learning has powerful capabilities of feature representation, and surpasses previous methods of feature representation based on the manual design in portraying the superiority of image features. Recently, deep learning methods have significantly affected on image reconstruction tasks [58]. The deep learning method is usually used to solve the spatial invariable motion blurring removal. These methods are largely concerned with estimating a blur kernel, and then the solution proceeds in the same way as non-blind deblurring. The kernel estimation based methods and direct image-to-image deblurring methods are two mainly categories.

(1) Blur kernel estimation methods

Table 1
A summary of traditional motion deblurring methods for image motion deblurring.

Basic theory	Author name	Method name	Advantages	Disadvantages	Ability for deblurring
Richardson-Lucy(R-L)	Yong et al. [32]	R-L with local prior	Suppress the ringing artifacts.	Loss of detail information for blurred image.	★★★
	Yang et al. [33]	GA-RL	Suppress the ringing artifacts and recover more detail information.	Cannot satisfy for general camera shake.	★★★
	Shah et al. [34]	R-L with weight calculation	Estimation accuracy of blur kernel is more in noiseless and in low noise condition.	Complex to achieve the method.	★★★★
	Sheng et al. [6]	R-L with depth-aware motion blur model	Applied to real-world images with the assistance of motion estimation.	Cannot solve video deblurring with nonuniform motion velocity assumption.	★★★★
Wiener filter	Vasu et al. [35]	Wiener filter method	Reduce the noise for optical image deblurring.	Time consuming and better deblurring result requirements.	★★★
	Shi et al. [37]	Linear deblurring with Wiener filter	Restore object image of different sizes and have high speed.	Proposed for specific scenarios and need better generalization performance.	★★★★
	Cai et al. [38]	Winner filter method	Deblurring for rotational movement image and photoelectric image.	Just for single image, and cannot used for video.	★★★
	Zhuang [42]	Knife-edge with Wiener filtering	Deblurring for 3D RFID tags.	Still in the laboratory research stage.	★★★★
Markov random field method	Abbadi et al. [45]	Markov basis with Laplace filter	Used for color and gray images deblurring.	Cannot solve deep blur estimation.	★★★★
	Zhen et al. [46]	Markov Random Field method	Used for depth spatially-varying image deblurring.	The scene cannot be texture less and translational blur dominates.	★★★
	Dhanakshirur [47]	Markov Random Field	Used for a dense non-uniform motion blur field.		★★★★
Variational Bayesian	Shao et al. [50]	Variational Bayesian	More adaptive sparse image prior with considerably less implementation heuristics.	The proposed approach are not the off-the-shelf non-informative prior.	★★★★
	Wipf et al. [51]	Variational Bayes for sparse priors	Success for blind deconvolution with a transparent platform for introducing enhancements and extensions.	The method is relatively complex.	★★★★
	Cao et al. [52]	Variational Bayesian estimation	Remove the effects of unknown camera shake.	Less of processing the relative motion between targets in an image.	★★★
Edge prediction	Xu et al. [54]	Gaussian filter for image edge prediction	Improve the deblurring result quality with adaptive regularization and able to blurred images with very large blur kernels.	Just useful for the blur image with clearly edge.	★★★
	Singh et al. [56]	Sobel filter for image edge prediction	Improve the running speed of the algorithm.	Longer training time is a significant limitation.	★★★★

Traditional motion blur estimation methods mostly assist motion blur estimation by recovering clear edge information from blurred images. Moreover, prior knowledge usually leads to complex optimization problems. In order to solve the above problems, motion blur estimation methods based on deep learning methods have been successively proposed for the motion blur kernel estimation. The process is shown in Fig. 4. The kernel estimation motion deblurring methods based on deep learning mainly estimate the motion vector kernel and frequency domain kernel.

1)Kernel estimation from the motion vector.

A spatially variant motion vector can be estimated by patch-wise classification, in which a neural network assigns probabilities to many candidate motion vectors. Sun et al. addressed the problem of estimating and removing non-uniform motion blur from a single blurry image [59]. This method estimated the probabilities of motion kernels at the patch level using a convolutional neural network (CNN). And, the patch-based estimation is used for a dense field of motion kernels by Markov random field (MRF). This patch-wise

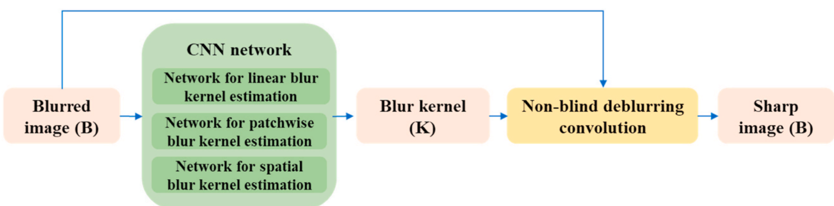

Fig. 4. Deep learning deblurring methods based on kernel estimation.

process is complicated and time-consuming. Then, a novel blur kernel estimation method based on regression model is proposed for motion blur estimation. The motion blur features are first mined through a convolutional neural network (CNN), and then mapped to motion length and orientation by support vector regression (SVR) [60]. This method is named CNNSVR, which gives more accurate kernel estimation and generate better deblurring result. Gong et al. proposed an motion blur to motion flow method [61] to directly estimate the motion flow from the blurred image through a fully-convolutional deep neural network (FCN) and recover the unblurred image from the estimated motion flow. The experimental results of synthetic and real-world data all show the strong deblurring ability for image. The motion kernel size estimation based on the CNN method is also used to restore sharp edges [62,63].

2) Kernel estimation in the frequency domain

Kernel estimation in the frequency domain has proved to be effective. A combination of learning-based feature extraction and kernel estimation of image deconvolution was proposed by Schuler et al. [64]. The network has modules for feature extraction, kernel estimation, and image reconstruction. Another method of estimating a blur kernel in the frequency domain is directly kernel co-efficients regression (FNN) [65]. The neural network infers the Fourier coefficients of the inverse filter from a blurred input image. There is also a cascade network, which uses three stacked modules perform multiple iterations to refine the features and the latent image. An attention mechanism is investigated for the blind deblurring NN, including both spatial and channel attention, to effectively handle the significant spatial variations on blurring effects [66,67].

(2) Direct image-to-image regression methods

Non-uniform blind deblurring for general dynamic scenes is a challenging computer vision problem. Recent studies have started to use end-to-end trainable networks for image and video deblurring [68]. The process is shown in Fig. 5. These methods also use multi-scale loss function that mimics conventional coarse-to-fine approaches and effectively solve the problem of image deblurring in dynamic scenes preliminary.

Considering the nature of the blurred process in the network structure design, Zhang et al. proposed a novel spatially variant neural network to solve different scene depths and dynamic scene [69]. This method embeds the recurrent neural network into a network structure based on encoder and decoder, and the coefficients of the recurrent neural network are realized by a network structure based on the encoder and decoder. For the problem of deblurring in a dynamic scene, a large number of end-to-end deep learning methods have been proposed in the later research [70–74]. In order to improve the end-to-end network model, some methods combined the fusing of prior knowledge in an end-to-end framework [75,76]. The results show that the fusion of prior knowledge can effectively constrain the deep learning model and make the deep learning model more compact and achieving better deblurring results.

The recent prosperity of generative adversarial networks(GAN) often yield sharper and more plausible textures than classical feed-forward encoder and witness success to deblurring by treating it as a special image-to-image translation task [77]. Kupyn et al. presented an end-to-end learned method for motion deblurring (DeblurGAN) [78]. The learning is based on a conditional GAN and the content loss. Then, Kupyn improved the DeblurGAN called as DeblurGAN-v2 [79]. DeblurGAN-v2 is based on a relativistic conditional GAN with a doublescale discriminator. This type of method considerably boosts state-of-the-art deblurring efficiency, quality, and flexibility.

The end-to-end deep learning method can be regarded as supervised learning. It needs lots of sharp images for the training. While, in a real world scene, it is difficult to obtain a sharp image at the simultaneously for the dynamic scene, as the camera or object motion. To solve this problem, un-supervised learning methods are proposed for the motion deblurring [80,81]. These methods achieved domain-specific and single-image deblurring by splitting the content and blurring features in a blurred image using content or using adversarial networks to synthesize blurred images.

We summarize neural network-based image motion deblurring techniques in Table 2, which covers the method name, advantages, disadvantages, and quality evaluation indices. The summarized content highlights that deep learning techniques are non-mechanistic approaches to image motion deblurring. These techniques employ expertly designed network structures with large numbers of parameters to simulate the relationship between original and blurred images, ultimately obtaining a blurred image reconstruction model. Different models possess varying deblurring capabilities, with the ultimate goal being a fast and effective solution for image motion deblurring. In these techniques, the motion deblurring stage is commonly considered as a part of the model, such as detection, tracking, and identification models. As a result, these techniques are well-suited for processing complex and dynamic scene images.

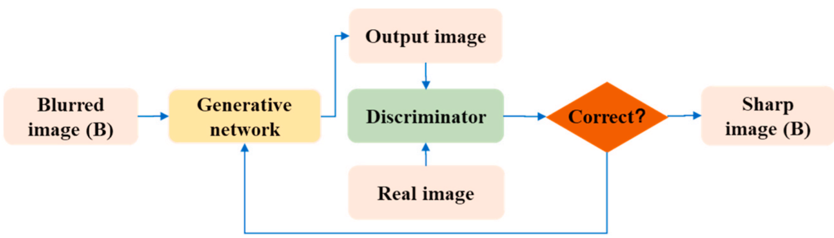

Fig. 5. Image-to-image deblurring methods based on deep learning.

Table 2
A summary deep learning method for image motion deblurring.

Author name	Method name	Advantages	Disadvantages	PSNR	MSE-motion
Sun et al. [59]	CNN	Motion blur kernel estimation for a dense scene.	Complicate and time-consuming.	44.55	7.83
Lu et al. [60]	CNNSVR	More accurate blur kernel estimation and generate better deblurring result by support vector regression (SVR).	Model structure complicate.	23.09	–
Gong et al. [61]	FCN	Fully-convolutional deep neural network for estimation of the motion flow directly.	Only designed for linear blur kernels, which limits the application domains.	21.95	1.05
Chakrabarti et al. [65]	FNN	Fourier coefficients of a deconvolution filter to be applied to the input patch for restoration.	Only for blind image deblurring.	–	3.01
Zhang et al. [69]	RNN	Determine network parameters through the relationship between the top and bottom of the pyramid.	Cannot calculate parallelly along the spatial dimension, so the inference time of this method is still not reduced.	29.19	–
Kupyn et al. [78]	DeblurGAN	The structure is relatively simple and the restoration result is more realistic.	High requirements for data sets.	28.7	–

In Table 2, we use the PSNR and MSE (both introduced in Section 3.4) as performance evaluation metrics for these methods to offer readers an understanding of their effectiveness and comparison. The larger the value of PSNR means the closer the restored image is to the original image, and the better the image restoration effect. And, the smaller the RMSE value means the better the restoration effect.

4.2. Quality evaluation index

Mass images are degraded due to blur and other factors. It is almost impossible to recognize and evaluate image quality by human eyes alone. The recognition of image quality through one or two mathematical models is also limited image processing. Therefore, the use of effective evaluation methods to evaluate image quality has important research significance. The evaluating the quality of image restoration in image deblurring is a basic task. The mainly evaluating index includes follows.

(1) With reference to image quality assessment

This type of method is based on the cumulative sum of errors. It is a full reference image quality evaluation, such as Root Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), etc. Most of the existing image deblurring methods for image quality evaluation using this kind of parameterized image quality evaluation method.

1) Root Mean Square Error (RMSE)

The basic idea of RMSE is to find the difference between the restored image and the original sharp image. Then calculate the sum of the squares of this difference and calculate the average as Eq. (5), and finally take the square root, which is expressed as Eq. (6):

$$MSE(\mathrm{x},\mathrm{y}) = \frac{1}{n \times m}\sum_{i=1}^{n\times m}(\mathrm{x}_i - \mathrm{y}_i)^2 \tag{5}$$

$$RMSE(\mathrm{x},\mathrm{y}) = \sqrt{MSE(\mathrm{x},\mathrm{y})} = \sqrt{\frac{1}{n \times m}\sum_{i=1}^{n\times m}(\mathrm{x}_i - \mathrm{y}_i)^2} \tag{6}$$

The original image $x \in R^{n\times m}$, the restoration image $y \in R^{n\times m}$. The greater the RMSE value means the greater the difference between restored and the original images. When using the mean square error to evaluate the image restoration effect, the smaller the RMSE value means the better the restoration effect.

2) Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio of the maximum possible power of the image to the corresponding noise power. It is based on the mean square error, due to the wide dynamic range of most signals. Therefore, the unit of PSNR is generally expressed as a logarithmic decibel of 10, specifically expressed as Eq. (7):

$$PSNR(\mathrm{x},\mathrm{y}) = 10\log_{10}\left(\frac{(2^n-1)^2}{MSE(\mathrm{x},\mathrm{y})}\right) = 20\log_{10}\left(\frac{\|2^n-1\|}{RMSE(\mathrm{x},\mathrm{y})}\right) \tag{7}$$

n is the number of bits for image store. The larger the value of PSNR means the closer the restored image is to the original image, and the better the image restoration effect.

3) Structural Similarity (SSIM)

The structural Similarity (SSIM) basic principle is to extract structural information from an image through the visual system of the human eye. Expressed as Eq. (8):

$$SSIM(\mathrm{x},\mathrm{y}) = \frac{(2\mu_x\mu_y + \mathrm{c}_1)(2\sigma_{xy} + \mathrm{c}_2)}{\left(\mu_x^2 + \mu_y^2 + \mathrm{c}_1\right)\left(\sigma_x^2 + \sigma_y^2 + \mathrm{c}_2\right)} \tag{8}$$

μ_x^2 and μ_y^2 represent the average value of the image. σ_x^2 and σ_y^2 represent the variance of the image. σ_{xy} represents the covariance between the original image and the clear image. Both c_1 and c_2 are constants, and the value range is $[-1,1]$. The larger the SSIM value means the more similar the restored image and the original clear image, and the better the restoration effect.

This kind of parameterized image quality evaluation index must provide good quality and clear reference or original image during evaluation. In general, the restoration image does not have such a reference image, so it cannot be applied to the image quality evaluation method without reference. Moreover, the original images in image deblurring are always unknown in practical applications.

(2) No-reference image quality assessment.

The conventional metrics, such as the peak signal-to-noise ratio (PSNR) and the mean-squared error (MSE) operate directly on the intensity of the image. They do not correlate well with the subjective fidelity ratings. Thus, many efforts have been made to design human visual system (HVS) based on IQA metrics and learning-based quality evaluation, called no-reference image quality assessment.

1) Human visual system (HSV)

The first category is based on the Human visual system (HSV). This method usually uses frequency-based decomposition, including contrast and directional sensitivity modeling, spatial and temporal mask effects, frequency selection, and color perception. Feature-similarity index (FSIM) is a no-reference image assessment based on HSV algorithm [82]. While, due to the complexity of HSV, these metrics can become very complex and computationally expensive.

2) Learning-based image quality evaluation

The learning-based quality evaluation assessment methods indicator based on natural scene statistics are: BRISQUE [83], BLIINDS [84], DIIVINE [85], and NIQE [86]. This type method extracts features from images through machine learning. Then use machine learning to obtain a good model, and finally use the trained model to predict the quality of the image. Due to the limitation of single model evaluation, more trends adopt fusion methods for learning evaluation.

4.3. Image motion deblurring datasets

The method of using neural network to restore image motion blur requires training to obtain network parameters. The datasets play an important role for deep learning methods in image motion deblurring. In reality, it is difficult to obtain motion blurred image datasets. According to the construction method of blurred datasets, it can be roughly divided into two categories, datasets of artificially synthesized and datasets of real scene.

(1) Synthesized datasets

1) Dataset with simulation blur kernel

This dataset is obtained by convolution of the sharp picture with simulation blur kernel, which built by Levin et al. [87] and Kupyn et al. [78]. Kupyn et al. proposed a method to simulate realistic and complex fuzzy kernels, following the idea of random trajectory generation. Then sub-pixel interpolation is applied to the trajectory vector to generate a kernel function.

2) Dataset with camera trajectory synthesis

The second category is blurred images synthesized by camera trajectory. This type of method uses a high-speed camera to continuously shoot and average the image to obtain a blurred image, such as Kohler [88]and GOPRO datasets. Nah et al. [89] proposed a realistic blury image dataset GOPRO, which chose to record the sharpening information to be integrated over time to generate the blurred image, and instead of modeling the kernel to convolve the sharpened image.

(2) Real scene datasets

1) Video Deblurring Dataset

Su et al. [90] built a benchmark which contains videos captured by various kinds of devices such as iPhone 6s, GoPro Hero 4 and Nexus 5*, and each video includes about 100 frames of size 1280*720. This benchmark consists of two sub datasets: quantitative and qualitative ones. The quantitative subset contains 6708 blurry frames and their corresponding ground-truth sharp frames from 71 videos. The qualitative subset includes 22 scenes, most of which contain more than 100 images.

2) Blurred KITTI Dataset

Geiger et al. [91] develop a dataset called KITTI by using their autonomous driving platform. The KITTI dataset consists of several subsets for various kinds of tasks, such as stereo matching, optical flow estimation, visual odometry, 3D object detection and tracking. Based on the stereo 2015 dataset in the KITTI dataset, Pan et al. [92] create a synthetic Blurred KITTI dataset, which contains 199 scenes. Each of the scenes includes 3 images captured by a left camera and 3 images captured by a right camera. This dataset is utilized only for testing. Comparison of the characteristics of mainstream data sets is shown in Table 3.

5. Applications of motion deblurring techniques in precision agriculture

Currently crop and livestock monitoring methods based on manual and computer vision cannot satisfy the requirements of precision agriculture due to the agriculture's unique environment and targets. The real-time and efficiency obtaining of image detail information has become an important and imperative part for modern agriculture production and management in a dynamic agriculture scene. Image motion deblurring technology can overcome camera shake or object motion to obtain g relatively sharp images and detail information for the computer vision task. Thus, image motion deblurring technology is vital for computer vision applications in precision agriculture.

The detail techniques and application areas are shown in Fig. 6, according to the paper section 4 content. As shown in Fig. 6 inside circle, the deep learning techniques are less than traditional deblurring techniques for motion deblurring. In contrast, the applications of deep learning motion deblurring are more than traditional methods in agriculture, owing to strong feature extraction ability of deep learning. Moreover, these techiques are mainly focus on detection and identification of plant species, identification of plant phenotyping, sorting and grading of harvest fruit, detection, biomass estimation and tracking of animal.

5.1. Precision fertilizer spreading

Excessive fertilizer use has been the main contributor to the increasing environmental imbalance observed in the past 20 years. Better accuracy and regular spreading of fertilizer are important to improve and maintain the nutritional element content of cultivated soils and limit excess fertilizer loss [93]. The management of mineral fertilization using centrifugal spreaders requires the development of spread pattern characterization devices to improve the quality of fertilizer spreading. The velocity of the granules when they leave the spinning disc is a major parameter for the spreading uniformity. While, the fast speed of the particles always causes blurred images and complicates for the information obtained from the precision fertilizer spreading [20]. Towards the fertilizer particle fast spreading speed, Villette et al. presented an optimized Hough transform method to extract the velocity information from motion deblurring image [94]. In this method, the author used a recursive linear filter inspired by the filter developed by Ziou [95] and modeled the filter by approximating an approximation Guassian second derivative to preprocess the original motion blurred image. Moreover, the peak extraction is carried out iteratively to identify the global maximum, deduce the line parameters and subtract from Hough space the Hough transform of the corresponding segment. This method is demonstrated that a motion blurred image acquired in the vicinity of the disc with a low cost imaging system can provide the three dimensional components of the outlet velocity of the particles.

Moreover, Villette et al. used the previous developed specific image processing method to estimate the mass flow and rotational speed affect fertilizer centrifugal spreading [96] and deduce the outlet angle from motion blurred image, which granule trajectories are identified [97]. For the measurement of the spread patterns of granular fertilizer spreaders, a global threshold operation was used to segment particles from the background and generate a particle binary image [98]. And then, this study used border following

Table 3
A summary for image motion deblurring datasets.

Type	Author Name	Dataset Name	Build approach	Advantage and disadvantage
Synthesized datasets	Levin et al.	LevinEtal Dataset	Simulate fuzzy kernels by different algorithms.	Easy to obtain, while local blurring is not considered.
	Kupyn et al.	Kupyn dataset	Simulate complex fuzzy kernels following the idea of random trajectory.	Easy to obtain and the motion in two-dimensional, while the real three-dimensional space is not considered.
	Kohler et al.	Kohler dataset	The movement trajectory is captured by a 6D camera.	The motion trajectory in three-dimensional space is collected, while the lens distortion and changes in depth of field are not considered.
	Nah et al.	GOPRO dataset	High-speed camera continuous shooting and average to obtain dataset.	Close to the real blur situation, while the acquisition process is troublesome and the data scene is single.
Real scene datasets	Su et al.	Deep video deblurring dataset	Build a dataset of real videos recorded with a high frame rate camera.	Useful for real world video deblurring. The scene is relatively comprehensive.
	Pan et al.	KITTI dataset	Build a Blurred KITTI dataset on realistic scenery with stereo camera and liner device.	Detailed and authentic for dataset, and usually used for deblurring methods testing,

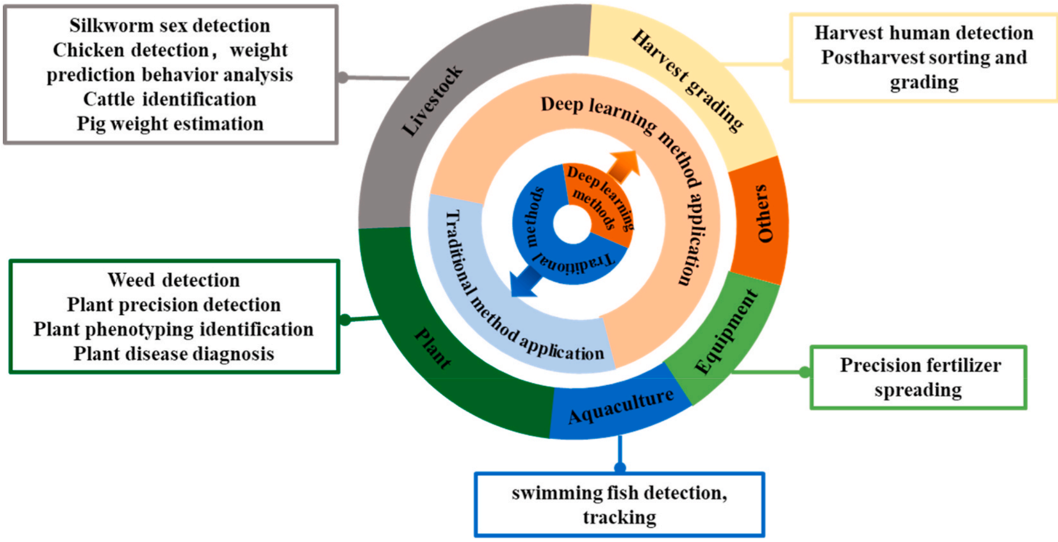

Fig. 6. Application of motion deblurring techniques in precision agriculture.

algorithm to determine the contours of the connected components for blur image particle trajectory segment. This method can solve the uncontrolled environment, the uniformity of the illumination and the black background problem of measuring the spread patterns of granular fertilizer spreaders. All the above methods are usually used in the original image preprocessing to remove the motion blur and provide precision information for the calculation of the different parameters.

5.2. Precision livestock farming

Livestock farming is an important part of the agriculture industry. As a basic animal husbandry industry, poultry farming plays an important role in promoting economic development, and ensuring increasing demands [1]. In modern livestock farming, management of livestock environment and animal welfare are two critical issues [99]. As an advanced and fundamental technology, computer vision has been widely used in livestock farming, such as detection, tracking and behavior analysis of animal. The statistical data proved that the motion and body deformation of feeding animal are the primary causes of the blurred image and bring errors [100], which roughly affect the application for computer vision. Thus, exploring the deblurring methods for the animal motion blur removal is essential.

(1) Silkworm sex detection

Machine vision-based technology has been applied for discriminating and sorting the sex of silkworm pupae. The motion blur of silkworm could lose textures and structures, e.g. edge and tail gonad, which is caused by the live silkworm pupa's writhing motion at the moment of capturing an image. Tao et al. toward this problem, presented a radon transform-based motion deblurring method for silkworm pupa image restoration [101]. The first sharp edges were acquired using filtering techniques in the image prediction stage. Then the initial blur kernel was computed with Gaussian prior. The coarse version latent image was deconvoluted in the Fourier domain. The Radon transform was applied to estimate the accurate kernel in the kernel refinement stage (Fig. 7). The radon transform of blur kernel k along straight lines which could be denoted using offset ρ and the orientation θ, as presented in follows Eq. (9).

$$\Phi_{\theta}^{k}(\rho) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} k(\mathrm{x},\mathrm{y})\delta(\rho - \mathrm{x}\cos(\theta) - \mathrm{y}\sin(\theta))dxdy \tag{9}$$

The $\Phi_{\theta}^{k}(\rho)$ denotes the projections of k along the direction orthogonal to different orientation θ.

Benefiting from the prediction step and the coarse-to-fine framework, the latent silkworm pupa image was recovered without ringing artifacts and edge-preserving.

(2) Farming broiler chicken detection and weight prediction

For broiler chicken farming, computer vision technology has been used in the chicken detection, weight prediction and other fields. Vilas et al. presented a general framework for live detection of broilers in poultry houses [102], which solved the crowded scenes, poor image quality and difficulty acquiring a benchmark of labeled samples. In this method, the author used a normalized box filter as the homogeneous blur (with a 9*9 uniform kernel) to preprocess the original blurred image and obtain high quality binary image. This step increased the accuracy of broiler detection. Wang et al. proposed an automated digestive disease detector based on a deep

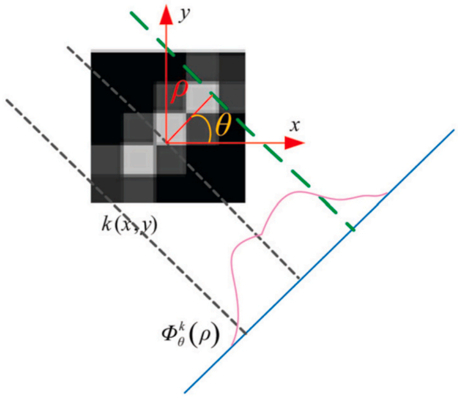

Fig. 7. Radon transform [101].

Convolutional Neural Network model to classify fine-grained abnormal broiler droppings images as normal and abnormal [103]. Because, the droppings images were obtained from the conveyor and usually blurred because of the conveyor movement. To solve this problem, Wang et al. used Gaussian, average, uniform and median blur to preprocess the motion blur image. The enhancement images promoted the disease droppings detection accuracy. In above methods, the Gaussian blur is show as Eq. (10), where σ is the standard deviation of normal distribution. The homogeneous blur and median blur are achieved through matrix convolution.

$$G(\mathrm{x},\mathrm{y}) = \frac{1}{2\pi\sigma^2} e^{-(\mathrm{x}^2+\mathrm{y}^2)/(2\sigma^2)} \tag{10}$$

Nasiri et al. presented a deep convolutional neural network that was used to detect and track seven key points on the bodies of walking broilers [104]. This method used deep learning strong learning ability to solve the motion blur. It achieved an overall classification accuracy of 95% and the average per-class classification accuracy was 97.5%. In addition, the broiler chickens' beak and head motion can provide fundamental information for the biomechanical. Yao et al. adopted an motion deblurring method called PSS-NSC, which is built by the Gao et al. [105] for the movement chicken motion blur image preprocessing [106]. This method proposes a which proposes a parameter-selective sharing mechanism to build a larger and higher-quality network framework, the method framework and deep learning structure shown in Fig. 8(a, b). Fig. 8a is the process of origin image pre-processing and Fig. 8b is framework of motion deblurring network. Then, this method used the database for the gender detection model training and obtained

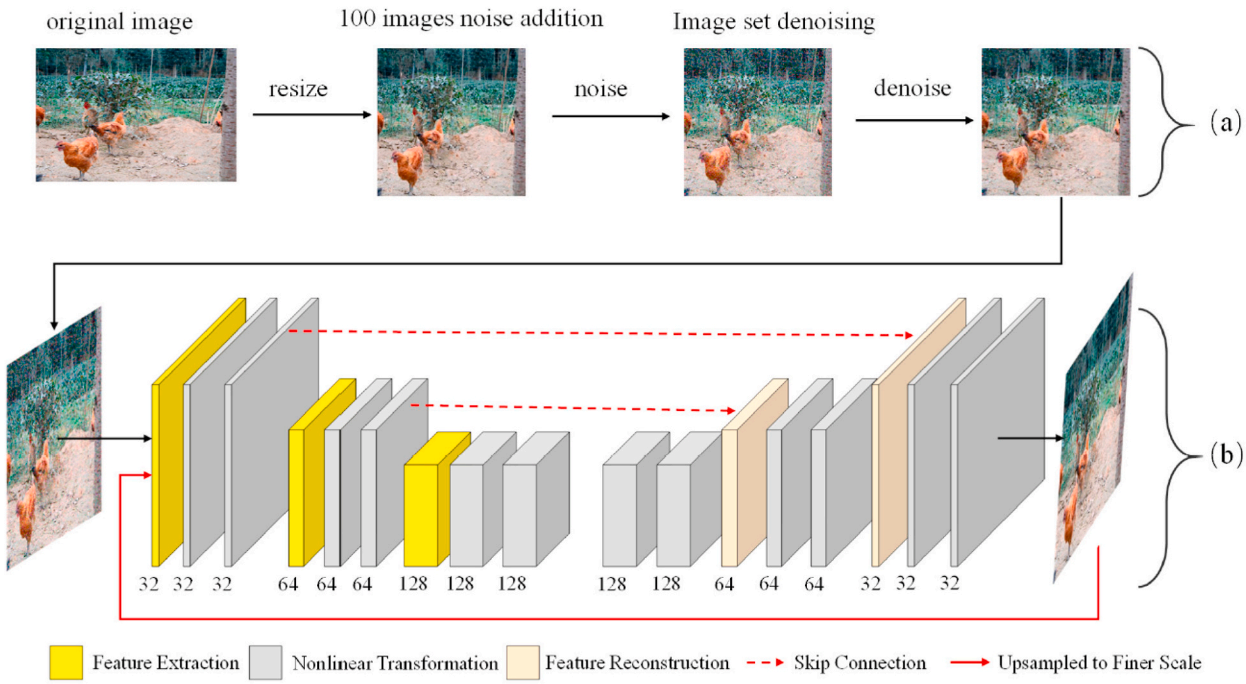

Fig. 8. The general framework of the image preprocessing process [106].

more accuracy results.

While, during the eating process, the higher speed of the beak creates a blurred image on the frame, which might lead the algorithm to errors due to difficulty precisely detecting the beak tip [100]. This part research is still unsolved for broiler chicken feeding. The proposed methods may have the potential to facilitate the efficient and repeatable acquisition of biomechanical data of broiler chickens during feeding.

(3) Swimming fish detection and tracking

Monitoring the growth condition and behavior of fish will enable scientific management and reduce the threat of losses caused by stress and disease [107]. Machine vision has been widely used as a noninvasive, portable, and effective method to sample and monitor fish. While, fish swimming always results in motion blur images and adds difficulty for detection, tracking and behavior analysis of fish [108]. For example, the behavior of cannibalism and the phenomenon of fish chasing brings the problem of motion blur. Towards this problem, Wang et al. proposed a real-time detection scheme based on the improved You Only Look Once YOLO-v5 to detect the cannibalism of grouper fry in recirculating aquaculture systems [16]. This method used multi-head attention in the backbone network to obtain global information, including the motion blurred image part, and effectively solve problems of motion blur, occlusion and small targets in the culture environment. Hu et al. also presented an improved YOLO-V4 network by modifying the feature map to de-redundancy for fish image deblurring [109]. Christensen et al. utilized a unified neural network that simultaneously performed bounding box and class predictions coupled with the application area with poorly conditioned environment, such as the motion blur, ununiformed illustration and low contrast light [4]. In this method, the authors presented an Optical Fish Detection Network (OFDNet), which consists of a Single Shot Multibox Detector (SSD). This method can identify the low visibility and motion blur clearly.

(4) Cattle detection and identification

Segmenting animals from video and tracking their motion is a prerequisite for body condition scoring and behavior analysis in precision livestock framing has been important in recent years. Kumar et al. used the face image to identify cattle using computer vision approaches [110]. The proposed method used Gaussian pyramid-based low-pass filtering technique to increase the image quality of cattle's face image. The preprocessing step can overcome the challenge of blurriness image, due to body dynamic of cattle. For cattle farming, an one-shot learning-based animal video segmentation method was proposed for movement cattle segmentation [111], shown in Fig. 9.

In this method, a post-processing step was adopted for image enhancement to remove the motion blur and other noise of cattle image. The post-processing step consists of test time augmentation and conditional random field for boosting and segmentation accuracy, which experiments on DAVIS 2016 animal data, achieved 89.5% at a relatively fast speed.

5.3. Precision weed detection

Weed control is a significant issue in agricultural crop production. Weeds compete with crop plants for moisture, nutrients and sunlight. They could have a detrimental impact on crop yields and quality if UN controlled. Computer vision technology has been used

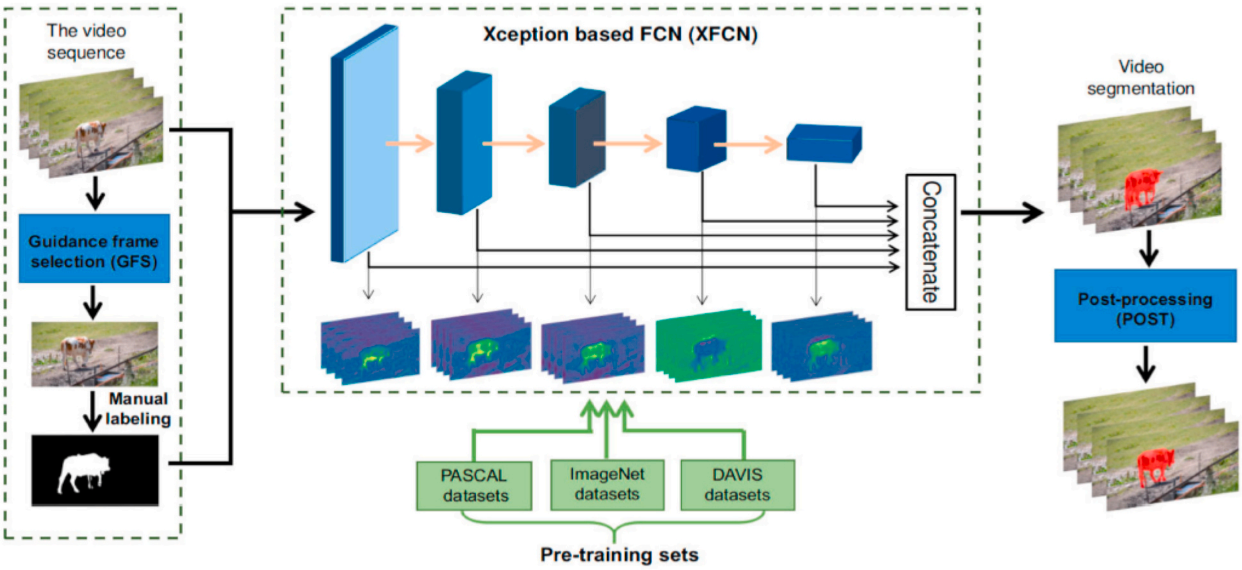

Fig. 9. Overall flowchart for one-shot learning-based animal video segmentation [111].

for weed identification by visual texture. However, real imaging systems are usually imperfect and the changing environmental conditions always result in a degraded image [112]. Image motion blur is an important class of degradations in practice. Peng et al. proposed a robust weed recognition scheme using low-quality color weed images with image deblurring method [18]. This method used image-moment-based blur invariant features to get the features invariant of the image scale but it is sensitive to camera motion. The normalized blur invariant features B are as follow Eq. (11) : The N is the size of image, and the sum of p and q is a constant to determine the set of blur invariant features.

$$B^1(\mathrm{p,q}) = B(\mathrm{p,q}) \,/\, \mathrm{u}_{00}(\mathrm{N}/2)^{p+q} \tag{11}$$

Buddha et al. outlined a robotic weed management system. They developed the image analysis portion of this system to overcome some real aerial difficulties such as motion blur [113]. They adopted the deblurGAN network [114] with a blind motion blur for deblur image super resolution. Hu et al. simulated the most common image degradation observed in weed mapping applications through the image formation pipeline. They and explored the influence, such as Gaussian noise, motion blur. This study used CNN methods, Faster R–CNN, Mask R–CNN and Deeplab-v3 for weed detection and instance segmentation. The CNN method can effectively reduce the influence of motion blur for weed image [115]. Above methods adopt different network structure. While, the implementation process are similar as shown in Figs. 4 and 5.

5.4. Intelligent postharvest sorting and grading

In the agriculture and food industry, the proper grading of fruits is very crucial to increase profitability [116]. Traditional manual experts for sorting the fruits are time-consuming, laborious, and suffer from the problem of inconsistency and inaccuracy in judgement by different human experts. In recent years, computer vision and image processing technologies have been applied for fruit sorting and grading. In fruit grading processing, the roller conveyor belt or the moving camera always produces a motion blur image, which add the difficulty for the grading image processing. An automatic electronic vision-based system for sorting and grading of fruit Mango. The wiener filtering method was used in this machine grading system to remove the motion deblurring [117]. Wiener filtering, also known as minimum mean square error filtering. The approximate formula can be expressed as follow Eq. (12). $H(\mathrm{x,y})$ is the degenerate function, $G(\mathrm{x,y})$ is the is the Fourier transform of the degraded image, $F^{'}$ is estimated image.

$$F^{'}(\mathrm{x,y}) = \left[\frac{1}{H(\mathrm{x,y})}\frac{|H(\mathrm{x,y})|^2}{|H(\mathrm{x,y})|^2 + K}\right]G(\mathrm{x,y}) \tag{12}$$

Currently, many fruit grading equipment increases the shutter speed to minimize the motion blur influence for object feature detection. Nandi et al. built a proposed model of a mango fruit system, and in the hardware part, the authors controlled and fixed the shutter speed to the value of 1/200s [118]. In order to remove the motion blur through methodology, Hu et al. adopt DeblurGAN method to deblur the apple images to improve the accuracy of apple feature extraction in the field [119], the basic processing frame can be shown in Fig. 5. This algorithm can stable solve the high feeding speed or apple moved rapidly resulting in a strong image blur deviation of the apple from the central channel, and extraction device operated stably and accurately grading the apples.

5.5. Plant precision detection and phenotyping identification

(1) Detection of plant

With the rise of artificial intelligence and machine learning in computer vision applications, images are a prime source of data that can help farmers improve management decision-making [120]. While for outdoor agriculture production, the dynamic environment and equipment movement make plant object detection or phenotyping identification still challenging tasks. A custom camera flash system using LEDs was developed and integrated into a machine vision platform in outdoor agriculture settings to overcome the sun's influence on apple detection by Mirhob et al. This system reduced the shutter duration on the camera to help to lessen the effect of motion blur when cameras captured images under high-velocity movement and ground vibrations. Yuan et al. used the popular method YOLOV4 convolution neural network for the outdoor and densely distributed apple flower detection [121] and zhang et al. as well used the YOLO5 method to develop a robust and real-time spear tips locator by improving image augmentation and lightweight network for selective harvesting robot of White asparagus [23]. These methods used deep learning methods preliminary to solve complex background and movement scene plant object detection difficulties, e.g. illumination, mirror, motion blur. For more complex scenes and higher speed object detection, Shah and Kumar proposed a scale recurrent network for deep image deblurring of grape detection. The result concluded that the proposed image deblurring method significantly improves the performance of grape detection on the corrupted motion blur dataset [19].

(2) Identification of plant phenotyping

In the last two decades, agriculture plant phenotyping has become the method of choice for quantitative assessment of plant morphology, development and function [122]. While, the dynamic optical appearance of developing plants, illumination shadow of inhomogeneous scene and equipment movement all add difficulties for automated segmentation of unimodal plant images. Especially, the plant leaf motion or the camera movement causes the image blur. This factor is a major factor for the detail phenotyping identification. Henke et al. presented an approach based on the co-registration of fluorescence and visible light camera images to automatic segmentation of greenhouse plant image [17]. This method used UN supervised k-means clustering of Eigen-colors is applied to generate a compact representation of pre-segmented visible light camera images to reduce the motion blur effects. Li et al. proposed a custom DCNN backbone, which is used as the first stage of the "two-stage" detector-Faster-RCNN to pre-train a model [123]. Furthermore, a confusion matrix of video detection is presented for the still rice disease image detection to solve the motion blur and defocus problems.

5. Discussion and future directions

Image motion deblurring is a cutting-edge problem in computational imaging filed. Currently, the traditional typical motion deblurring methods, such as RL, WF and MAF cannot satisfy the demand for precision agriculture applications. Given the complex agricultural environment and the difficulty of parameterizing spatially varying blur kernels in realistic imaging, it is crucial to study unrestricted nonparametric blind image motion deblurring in the context of real agricultural applications. Although deep learning deblurring techniques have shown significant progress in image motion blur removal, existing methods still have limitations, whether in terms of restoration model intuition, estimation accuracy, robustness, or algorithm efficiency. Therefore, an extended discussion on the pressing topic of nonparametric image deblurring is presented as follows.

(1) Data-driven deep representation learning techniques will be essential for image motion deblurring in realistic agricultural scenes and complex environments. The research on data-driven deblurring and deep representation learning began later but has progressed rapidly in recent years. Although deep neural networks possess inherent computational advantages due to end-to-end training, their generalization performance needs improvement compared to traditional motion image deblurring methods, and they suffer from poor comprehensibility. As a result, the supervised deep learning approach should be enhanced by combining it with mechanism analysis models for unrestricted nonparametric blind deblurring problems in real-world agricultural scenes. Additionally, exploring nonparametric deblurring methods based on unsupervised deep learning could be a promising choice for agricultural image processing.

In recent years, unsupervised deep learning models, represented by GANs, have gained popularity. Thus, integrating the Maximum a Posteriori (MAP) blind deblurring method with Deep Reinforcement Learning (DRL), and incorporating the complementary benefits of both MAP and DRL algorithms is a crucial scientific problem worthy of attention for motion image deblurring. Furthermore, achieving a fast and robust blind deblurring algorithm for salient edge depth perception, guided by the variation mechanism in precision agriculture, will also be an essential advancement.

(2) Spatial changes and irregular deformations of agricultural organisms are the primary challenges for image motion deblurring in precision agriculture. In agriculture and aquaculture, the primary targets are living organisms, including animals and plants. Animals often exhibit rapid movements and non-rigid morphological changes, while plants are typically affected by external factors such as wind and human intervention. These motion characteristics result in spatial blur, multi-scale targets, and edge blur expansion. Moreover, imaging devices may also cause blurring due to spatial changes resulting from their translation, rotation, and swing during practical agricultural production. Handheld cameras capturing on-site emergency scenes and high-speed moving targets recorded by airborne cameras can introduce more complex motion blur, posing greater challenges to the deblurring problem.

Although traditional variational methods combined with target segmentation have begun to address the problem of dynamic space-varying blur, these methods only consider single blur targets and blur types and introduce additional computational complexity due to blur target segmentation. Dynamic deblurring methods based on deep learning face considerable challenges, including issues with supervised training and poor generalization performance. Consequently, improving space-invariant deblurring algorithms to adapt to dynamic motion deblurring problems involving spatial changes remains a critical scientific problem that requires a solution.

(3) Overcoming motion blur caused by fast-moving equipment is a significant challenge for detecting static targets and extracting features in agricultural settings. Unlike living organism's motion blur, the target is usually static. Simultaneously, the capture device moves rapidly to ensure production efficiency, resulting in motion blur. Therefore, algorithm efficiency is crucial for scenarios with high real-time requirements. The computational speed of an algorithm plays an essential role in its practical application. In contrast, traditional image deblurring methods often face low computational efficiency and susceptibility to ringing and noise. Consequently, enhancing the real-time performance of image motion blur reduction algorithms can make these techniques applicable to a broader range of settings. For instance, during the production monitoring process, a real-time image motion blur reduction algorithm can capture images while objects are in motion. This eliminates the need to stop the item, thereby increasing the efficiency of the production line.

(4) Different blurred image datasets are essential for precision agriculture**.** Blurred image datasets significantly affect the performance of deep learning methods in image enhancement. Presently, the availability and variety of open-source datasets are limited. The most popular and extensive dataset, GOPRO, contains only 2103 pairs of training images and 1111 pairs of test images. This is far less than the datasets available in other computer vision fields, especially when compared to the ImageNet dataset, which includes 14,197,122 images. Contrary to the areas of image recognition and segmentation, acquiring agriculture blurred image datasets can be quite challenging. Regardless, datasets function as the foundation for researchers in any field to make advancements. The scarcity of these datasets directly impacts the progress of research in this area. As a result, there is an urgent need to introduce a large-scale, innovative and different types agriculture datasets that addresses this gap.

6. Conclusion

The rapid development of computer vision, image processing and deep learning technology has greatly benefited the precision agriculture by offering cost-effective, non-destructive assessment tools. However, real-world agricultural settings often present complex challenges such as fast animal movements, equipment vibrations, and environmental influences which can cause motion-blurred images and reduce the effectiveness of these technologies. This makes the computer vision tasks of precision agriculture such as detection, tracking and behavior analysis of animals, as well as detection and identification of plants, difficult even with high shutter speed cameras.

Image motion deblurring has emerged as a crucial technology for motion-blurred image reconstruction and has the potential of significantly enhancing the capabilities of agricultural image analysis. Mathematically, it is feasible to reconstruct an underlying image from a motion-blurred one and reveal hidden information within the data. However, image deblurring is inherently an ill-posed problem due to the numerous unknown parameters involved, making it a challenging task. The dynamic nature of the agricultural environment and the movements and deformation of livestock animals further complicate the problem. These challenges underline the significant demand for more effective and robust image motion deblurring techniques that can tackle complex and dynamic agricultural scenarios, ultimately contributing to the advancements in precision agriculture.

This study provides a detailed introduction to both traditional and current deep learning techniques for motion image deblurring. We also discuss various types of deblurring methods, including their basic theories, advantages and disadvantages, and motion image deblurring capabilities, aiming to encourage more researchers to apply these methods to address existing agricultural challenges. Furthermore, we highlight the future directions of motion image deblurring in precision agriculture, inspiring researchers to develop improved motion deblurring techniques to enhance accuracy and monitoring in the field of precision agriculture.

Author contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

Data availability statement

No data was used for the research described in the article.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the National Natural Science Foundation of China “Intelligent identification method of underwater fish morphological characteristics based on binocular vision” (No. 62206021), Beijing Digital Agriculture Innovation Consortium Project (No. BAIC10-2022) and the National Natural Science Foundation of China “Analysis and feature recognition on feeding behavior of fish school in facility farming based on machine vision” (No. 62076244).

References

[1] D. Wu, D. Cui, M. Zhou, Y. Ying, Information perception in modern poultry farming: a review, Comput. Electron. Agric. 199 (2022), 107131, https://doi.org/10.1016/j.compag.2022.107131.
[2] D. Li, Z. Song, C. Quan, X. Xu, C. Liu, Recent advances in image fusion technology in agriculture, Comput. Electron. Agric. 191 (2021), 106491, https://doi.org/10.1016/j.compag.2021.106491.
[3] Z. Zhan, X. Yang, Y. Li, C. Pang, Video deblurring via motion compensation and adaptive information fusion, Neurocomputing 341 (2019) 88–98, https://doi.org/10.1016/j.neucom.2019.03.009.
[4] J.H. Christensen, L.V. Mogensen, R. Galeazzi, J.C. Andersen, Detection, Localization and Classification of Fish and Fish Species in Poor Conditions Using Convolutional Neural Networks, IEEE, 2018, p. 1.
[5] H. Yu, K. Lee, G. Morota, Forecasting dynamic body weight of nonrestrained pigs from images using an RGB-D sensor camera, Translational Animal Science 5 (1) (2021) 1–9, https://doi.org/10.1093/tas/txab006.
[6] B. Sheng, P. Li, X. Fang, P. Tan, E. Wu, Depth-Aware motion deblurring using loopy belief propagation, Ieee T Circ Syst Vid 30 (4) (2020) 955–969, https://doi.org/10.1109/TCSVT.2019.2901629.
[7] B. Hua, K. Low, Interactive motion deblurring using light streaks. 2011 18th (IEEE), IEEE International Conference on Image Processing 1 (2011).
[8] T.H. Kim, S. Nah, K.M. Lee, Dynamic video deblurring using a locally adaptive blur model, Ieee T Pattern Anal 40 (10) (2018) 2374–2387, https://doi.org/10.1109/TPAMI.2017.2761348.
[9] S. Cho, Y. Matsushita, S. Lee, Removing non-uniform motion blur from images (IEEE), IEEE International Conference on Computer Vision IEEE 1 (2007).
[10] M. Ben-Ezra, S.K. Nayar, Motion-Based motion deblurring, Ieee T Pattern Anal (2004) 689–697.
[11] R. Wang, D. Tao, Recent Progress in Image Deblurring. Computer Vision and Pattern Recognition (cs.CV), 2014.

[12] W. Shen, W. Bao, G. Zhai, L. Chen, X. Min, Z. Gao, Video frame interpolation and enhancement via pyramid recurrent framework, Ieee T Image Process 30 (2021) 277–292, https://doi.org/10.1109/TIP.2020.3033617.
[13] D.A. Borges Oliveira, L.G. Ribeiro Pereira, T. Bresolin, R.E. Pontes Ferreira, J.R. Reboucas Dorea, A review of deep learning algorithms for computer vision systems in livestock, Livest. Sci. 253 (2021), 104700, https://doi.org/10.1016/j.livsci.2021.104700.
[14] Z. Li, R. Guo, M. Li, Y. Chen, G. Li, A review of computer vision technologies for plant phenotyping, Comput. Electron. Agric. 176 (2020), 105672, https://doi.org/10.1016/j.compag.2020.105672.
[15] H. Chopra, H. Singh, M.S. Bamrah, F. Mahbubani, A. Verma, N. Hooda, et al., Efficient fruit grading system using spectrophotometry and machine learning approaches, Ieee Sens J 21 (14) (2021) 16162–16169, https://doi.org/10.1109/JSEN.2021.3075465.
[16] H. Wang, S. Zhang, S. Zhao, J. Lu, Y. Wang, D. Li, et al., Fast detection of cannibalism behavior of juvenile fish based on deep learning, Comput. Electron. Agric. 198 (2022), 107033, https://doi.org/10.1016/j.compag.2022.107033.
[17] M. Henke, A. Junker, K. Neumann, T. Altmann, E. Gladilin, A two-step registration-classification approach to automated segmentation of multimodal images for high-throughput greenhouse plant phenotyping, Plant Methods 16 (1) (2020), https://doi.org/10.1186/s13007-020-00637-x.
[18] Z. Peng, C. Jun, Weed recognition using image blur information, 2011, Biosyst. Eng. 110 (2) (2011) 198–205, https://doi.org/10.1016/j.biosystemseng.08.003.
[19] M. Shah, P. Kumar, Improved handling of motion blur for grape detection after deblurring. 8th international conference on signal processing and integrated networks (SPIN) (IEEE), IEEE 1 (2021).
[20] S. Villette, F. Cointault, P. Zwaenepoel, B. Chopinet, M. Paindavoine, Velocity Measurement Using Motion Blurred Images to Improve the Quality of Fertiliser Spreading in Agriculture, SPIE, 2007, p. 1.
[21] A.K. Rangarajan, E.J. Balu, M.S. Boligala, A. Jagannath, B.N. Ranganathan, A low-cost UAV for detection of Cercospora leaf spot in okra using deep convolutional neural network, Multimed. Tool. Appl. 81 (15) (2022) 21565–21589, https://doi.org/10.1007/s11042-022-12464-4.
[22] W.H. Richardson, Bayesian-Based iterative method of image restorat, J. Opt. Soc. Am. 62 (1) (1972) 55–59.
[23] P. Zhang, X. Liu, J. Yuan, C. Liu, YOLO5-spear: a robust and real-time spear tips locator by improving image augmentation and lightweight network for selective harvesting robot of white asparagus, Biosyst. Eng. 218 (2022) 43–61, https://doi.org/10.1016/j.biosystemseng.2022.04.006.
[24] S. Cho, Y. Matsushita, S. Lee, Removing non-uniform motion blur from images (IEEE), IEEE International Conference on Computer Vision 1 (2007).
[25] Y. Yitzhaky, N.S. Kopeika, Identification of blur parameters from motion blurred images, Graph. Model. Image Process. 59 (5) (1997) 310–320, https://doi.org/10.1006/gmip.1997.0435.
[26] V. Katkovnik, K. Egiazarian, J. Astola, A spatially adaptive nonparametric regression image deblurring, Ieee T Image Process 14 (10) (2005) 1469–1478, https://doi.org/10.1109/TIP.2005.851705.
[27] T. Askari Javaran, H. Hassanpour, V. Abolghasemi, Local motion deblurring using an effective image prior based on both the first- and second-order gradients, Mach. Vis. Appl. 28 (3–4) (2017) 431–444, https://doi.org/10.1007/s00138-017-0824-8.
[28] Z. Hu, S. Cho, J. Wang, M. Yang, Deblurring Low-Light images with light streaks, Ieee T Pattern Anal 40 (10) (2018) 2329–2341, https://doi.org/10.1109/TPAMI.2017.2768365.
[29] R. Fergus, B. Singh, A. Hertzmann, S.T. Roweis, W.T. Freeman, Removing camera shake from a single photograph, Acm T Graphic 25 (3) (2006) 787–794.
[30] L.B. Lucy, An iterative technique for the rectification of observed distributions, Astron. J. 79 (1974) 745.
[31] N. Wiener, Extrapolation, Interpolation, and Smoothing of Stationary Time Series, MIT press Cambridge, 1949.
[32] W. Yongpan, F. Huajun, X. Zhihai, L. Qi, D. Chaoyue, An improved Richardson–Lucy algorithm based on local prior, Opt Laser. Technol. 42 (5) (2010) 845–849, https://doi.org/10.1016/j.optlastec.2010.01.001.
[33] H. Yang, P. Huang, S. Lai, A novel gradient attenuation Richardson–Lucy algorithm for image motion deblurring, Signal Process. 103 (2014) 399–414, https://doi.org/10.1016/j.sigpro.2014.01.023.
[34] M.J. Shah, U. Dalal, Single-shot blind uniform motion deblurring with ringing reduction, Imag. Sci. J. 65 (8) (2017) 484–499, https://doi.org/10.1080/13682199.2017.1366614.
[35] R.M. Vasu, V. Boopathi, Deblurring in a noncoherent optical processing system: pupil function synthesis and experimental implementation, 1994, Opt. Eng. 33 (6) (1994) 1953–1961.
[36] R.M. Vasu, G.L. Rogers, Construction of a phase-inverting grating and its use in a deblurring filter, Appl. Opt. (3) (1980) 469–473, https://doi.org/10.1364/AO.19.000469.
[37] Y. Shi, B. He, M. Zhu, L. Zhang, Fast linear motion deblurring for 2D barcode, Optik 219 (2020), 164902, https://doi.org/10.1016/j.ijleo.2020.164902.
[38] C. Cai, A. Liu, B. Zhang, Motion Deblurring from a Single Image. 2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD), IEEE, 2016.
[39] M. Welk, P. Raudaschl, T. Schwarzbauer, M. Erler, M. Läuter, Fast and Robust linear motion deblurring, Signal, Image and Video Processing 9 (5) (2015) 1221–1234, https://doi.org/10.1007/s11760-013-0563-x.
[40] Y. Qian, F. Hu, X. Cheng, W. Jin, Real-time image deblurring by optoelectronic hybrid processing, Applied optics. Optical technology and biomedical optics 50 (33) (2011) 6184.
[41] B. Oswald-Tranta, M. Sorger, P. O Leary, Motion deblurring of infrared images from a microbolometer camera, Infrared Phys Techn 53 (4) (2010) 274–279, https://doi.org/10.1016/j.infrared.2010.04.003.
[42] X. Zhuang, X. Yu, D. Zhou, Z. Zhao, W. Zhang, L. Li, et al., A novel 3D position measurement and structure prediction method for RFID tag group based on deep belief network, Measurement 136 (2019) 25–35, https://doi.org/10.1016/j.measurement.2018.12.071.
[43] K. Yamamoto, M. Onuki, Y. Tanaka, Non-Blind deconvolution of point cloud attributes in graph spectral domain, IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences. E100.A (9) (2017) 1751–1759, https://doi.org/10.1587/transfun.E100.A.1751.
[44] J. Woo, E.Z. Murano, M. Stone, J.L. Prince, Reconstruction of High-Resolution tongue volumes from MRI, Ieee T Bio-Med Eng. 59 (12) (2012) 3511–3524, https://doi.org/10.1109/TBME.2012.2218246.
[45] N. El Abbadi, E.J. Al Taee, Z. Abdulsamad, Improve image de-blurring, International Conference on Innovative Trends in Computer Engineering (ITCE) (2018) 25–30.
[46] R. Zhen, R.L. Stevenson, Motion Deblurring and Depth Estimation from Multiple Images, IEEE, 2016, p. 1.
[47] R.R. Dhanakshirur, R.A. Tabib, U. Patil, Evidence based feature selection and collaborative representation towards learning based PSF estimation for motion deblurring, IEEE/CVF International Conference on Computer Vision (ICCV) (2019) 1008–1016, https://doi.org/10.1109/ICCVW.2019.00130.
[48] J. Sun, W. Cao, Z. Xu, J. Ponce, Learning a Convolutional Neural Network for Non-uniform Motion Blur Removal, 2015.
[49] A. Levin, Y. Weiss, F. Durand, W.T. Freeman, Understanding blind deconvolution algorithms, Ieee T Pattern Anal 33 (12) (2011) 2354–2367, https://doi.org/10.1109/TPAMI.2011.148.
[50] W. Shao, H. Deng, Q. Ge, H. Li, Z. Wei, Regularized motion blur-kernel estimation with adaptive sparse image prior learning, Pattern Recogn. 51 (2016) 402–424, https://doi.org/10.1016/j.patcog.2015.09.034.
[51] D. Wipf, H. Zhang, Revisiting bayesian blind deconvolution, J. Mach. Learn. Res. 15 (2014) 3775–3814.
[52] S. Cao, N. He, S. Zhao, K. Lu, X. Zhou, Single image motion deblurring with reduced ringing effects using variational Bayesian estimation, Signal Process. 148 (2018) 260–271, https://doi.org/10.1016/j.sigpro.2018.02.015.
[53] L. Yang, H. Ji, A variational EM framework with adaptive edge selection for blind motion deblurring, IEEE/CVF Conference on Computer Vision and Pattern Recognition (2019) 10159–10168, https://doi.org/10.1109/CVPR.2019.01041.
[54] L. Xu, J. Jia, Two-Phase Kernel Estimation for Robust Motion Deblurring. 11th European Conference on Computer Vision 2010, Springer Berlin Heidelberg, Berlin, Heidelberg, 2010, pp. 157–170.
[55] S. Cho, S. Lee, Fast Motion Deblurring, European conference on computer vision, 2010, pp. 157–170.

[56] V. Singh, K. Ramnath, A. Mittal, Refining high-frequencies for sharper super-resolution and deblurring, Comput Vis Image Und 199 (2020), 103034, https://doi.org/10.1016/j.cviu.2020.103034.
[57] W. Shao, Q. Ge, H. Deng, Z. Wei, H. Li, Motion deblurring using non-stationary image modeling, J. Math. Imag. Vis. 52 (2) (2015) 234–248, https://doi.org/10.1007/s10851-014-0537-9.
[58] J. Koh, J. Lee, S. Yoon, Single-image deblurring with neural networks: a comparative survey, Comput Vis Image Und 203 (2021), 103134, https://doi.org/10.1016/j.cviu.2020.103134.
[59] J. Sun, W. Cao, Z. Xu, J. Ponce, Learning a convolutional neural network for non-uniform motion blur removal, IEEE (2015) 769–777.
[60] Y. Lu, X. Fengying, Z. Jiang, Kernel estimation for motion blur removal using deep learning convolutional neural network, IEEE International Conference on Image Processing (ICIP) IEEE (2017) 3755–3759.
[61] D. Gong, J. Yang, L. Liu, Y. Zhang, I. Reid, C. Shen, et al., From Motion Blur to Motion Flow: A Deep Learning Solution for Removing Heterogeneous Motion Blur. 2017 IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 3806–3815, https://doi.org/10.1109/CVPR.2017.405.
[62] X. Xu, J. Pan, Y. Zhang, M. Yang, Motion blur kernel estimation via deep learning, Ieee T Image Process 27 (1) (2018) 194–205, https://doi.org/10.1109/TIP.2017.2753658.
[63] L. Li, N. Sang, L. Yan, C. Gao, Motion-blur kernel size estimation via learning a convolutional neural network, Pattern Recogn. Lett. 119 (2019) 86–93, https://doi.org/10.1016/j.patrec.2017.08.017.
[64] C.J. Schuler, M. Hirsch, S. Harmeling, B. Scholkopf, Learning to deblur, Ieee T Pattern Anal 38 (7) (2016) 1439–1451, https://doi.org/10.1109/TPAMI.2015.2481418.
[65] A. Chakrabarti, A Neural Approach to Blind Motion Deblurring, European Conference on Computer Vision, 2016, pp. 221–235, https://doi.org/10.1007/978-3-319-46487-9.
[66] Q. Qi, J. Guo, W. Jin, Attention network for Non-Uniform deblurring, IEEE Access 8 (2020) 100044–100057, https://doi.org/10.1109/ACCESS.2020.2997408.
[67] Y. Xu, Y. Zhu, Y. Quan, H. Ji, Attentive deep network for blind motion deblurring on dynamic scenes, Comput Vis Image Und 205 (2021) 1–12, https://doi.org/10.1016/j.cviu.2021.103169.
[68] X. Tao, H. Gao, Y. Wang, X. Shen, J. Wang, J. Jia, Scale-recurrent Network for Deep Image Deblurring, IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018.
[69] J. Zhang, J. Pan, J. Ren, Y. Song, Dynamic Scene Deblurring Using Spatially Variant Recurrent Neural Networks. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 1–9.
[70] Y. Yuan, W. Su, D. Ma, Efficient dynamic scene deblurring using spatially variant deconvolution network with optical flow guided training, IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020) 3552–3561, https://doi.org/10.1109/CVPR42600.2020.00361.
[71] M. Suin, K. Purohit, A.N. Rajagopalan, Spatially-Attentive Patch-Hierarchical network for adaptive motion deblurring, IEEE Conference on Computer Vision and Pattern Recognition (2020) 3603–3612.
[72] R. Aljadaany, D.K. Pal, M. Savvides, Douglas-Rachford networks: learning both the image prior and data fidelity terms for blind image deconvolution, IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019) 10235–10244, https://doi.org/10.1109/CVPR.2019.01048.
[73] H. Zhang, Y. Dai, H. Li, P. Koniusz, Deep Stacked Hierarchical Multi-Patch Network for Image Deblurring. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 5971–5979, https://doi.org/10.1109/CVPR.2019.00613.
[74] H. Gao, X. Tao, X. Shen, J. Jia, Dynamic scene deblurring with parameter selective sharing and nested skip connections, IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2019) 3848–3856, https://doi.org/10.1109/CVPR.2019.00397.
[75] J. Pan, J. Dong, Y. Liu, J. Zhang, J. Ren, J. Tang, et al., Physics-Based generative adversarial models for image restoration and beyond, IEEE Trans. Pattern Anal. Mach. Intell. (2020), https://doi.org/10.1109/TPAMI.2020.2969348.
[76] S. Lin, J. Zhang, J. Pan, Y. Liu, Y. Wang, J. Chen, et al., Learning to deblur face images via sketch synthesis, Proc. AAAI Conf. Artif. Intell. 34 (7) (2020) 11523–11530, https://doi.org/10.1609/aaai.v34i07.6818.
[77] P. Isola, J. Zhu, T. Zhou, A.A. Efros, Image-to-Image translation with conditional adversarial networks, IEEE Conference on Computer Vision and Pattern Recognition (2017) 5967–5976, https://doi.org/10.1109/CVPR.2017.632.
[78] O. Kupyn, V. Budzan, M. Mykhailych, D. Mishkin, J. Matas, DeblurGAN: blind motion deblurring using conditional adversarial networks, IEEE/CVF Conference on Computer Vision and Pattern Recognition (2018) 8183–8192, https://doi.org/10.1109/CVPR.2018.00854.
[79] O. Kupyn, T. Martyniuk, J. Wu, Z. Wang, DeblurGAN-v2: Deblurring (Orders-Of-Magnitude) Faster and Better, IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 8877–8886, https://doi.org/10.1109/ICCV.2019.00897.
[80] B. Lu, J. Chen, R. Chellappa, Unsupervised Domain-specific Deblurring via Disentangled Representations. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 10217–10226, https://doi.org/10.1109/CVPR.2019.01047.
[81] N.T. Madam, S. Kumar, A.N. Rajagopalan, Unsupervised Class-specific Deblurring, European Conference on Computer Vision, 2018, pp. 358–374.
[82] L. Zhang, L. Zhang, X. Mou, D. Zhang, FSIM: a feature similarity index for image quality assessment, IEEE Trans. Image Process. 20 (8) (2011) 2378–2386, https://doi.org/10.1109/TIP.2011.2109730.
[83] A. Mittal, A.K. Moorthy, A.C. Bovik, No-Reference image quality assessment in the spatial domain, Ieee T Image Process 21 (12) (2012) 4695–4708, https://doi.org/10.1109/TIP.2012.2214050.
[84] M.A. Saad, A.C. Bovik, C. Charrier, Blind image quality assessment: a natural scene statistics approach in the DCT domain, Ieee T Image Process 21 (8) (2012) 3339–3352, https://doi.org/10.1109/TIP.2012.2191563.
[85] A.K. Moorthy, A.C. Bovik, Blind image quality assessment: from natural scene statistics to perceptual quality, Ieee T Image Process 20 (12) (2011) 3350–3364, https://doi.org/10.1109/TIP.2011.2147325.
[86] A. Mittal, R. Soundararajan, A.C. Bovik, Making a "completely blind" image quality analyzer, IEEE Signal Process. Lett. 20 (3) (2013) 209–212, https://doi.org/10.1109/LSP.2012.2227726.
[87] A. Levin, Y. Weiss, F. Durand, W.T. Freeman, Understanding and Evaluating Blind Deconvolution Algorithms, IEEE, 2009, p. 1.
[88] R. Köhler, M. Hirsch, B. Mohler, B. Schölkopf, S. Harmeling, Recording and Playback of Camera Shake: Benchmarking Blind Deconvolution with a Real-World Database, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 27–40.
[89] S. Nah, T.H. Kim, K.M. Lee, Deep Multi-Scale Convolutional Neural Network for Dynamic Scene Deblurring, IEEE Computer Society., 2016, pp. 3883–3891.
[90] S. Su, M. Delbracio, J. Wang, Deep Video Deblurring for Hand-Held Cameras. IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 238–246, https://doi.org/10.1109/CVPR.2017.33.
[91] A. Geiger, P. Lenz, C. Stiller, R. Urtasun, Vision meets robotics: the KITTI dataset, Int. J. Robot Res. 32 (11) (2013) 1231–1237, https://doi.org/10.1177/0278364913491297.
[92] L. Pan, Y. Dai, M. Liu, F. Porikli, Simultaneous Stereo Video Deblurring and Scene Flow Estimation. 2017 IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 6987–6996, https://doi.org/10.1109/CVPR.2017.739.
[93] B. Hijazi, F. Cointault, J. Dubois, S. Coudert, J. Vangeyte, J. Pieters, et al., Multi-phase cross-correlation method for motion estimation of fertiliser granules during centrifugal spreading, Precis. Agric. 11 (6) (2010) 684–702, https://doi.org/10.1007/s11119-010-9193-2.
[94] S. Villette, F. Cointault, E. Piron BC, M. Paindavoine, A simple imaging system to measure velocity and improve the quality of fertilizer spreading in agriculture, Journal of Electronic Image (2008) 1109–1119.
[95] D. Ziou, Line Detection Using an Optical IIR Filter, Pattern Recogn, 1991, pp. 465–478.
[96] S. Villette, E. Piron, D. Miclet, R. Martin, G. Jones, J. Paoli, et al., How mass flow and rotational speed affect fertiliser centrifugal spreading: potential interpretation in terms of the amount of fertiliser per vane, Biosyst. Eng. 111 (1) (2012) 133–138, https://doi.org/10.1016/j.biosystemseng.2011.11.003.
[97] S. Villette, E. Piron, R. Martin, D. Miclet, G. Jones, J. Paoli, et al., Estimation of two-dimensional fertiliser mass flow distributions by recording granule impacts, Biosyst. Eng. 115 (4) (2013) 463–473, https://doi.org/10.1016/j.biosystemseng.2013.05.008.

[98] S. Cool, J. Pieters, D. Seatovic, K. Mertens, D. Nuyttens, T. Van De Gucht, et al., Development of a Stereovision-Based technique to measure the spread patterns of granular fertilizer spreaders, Sensors-Basel. 17 (6) (2017) 1396, https://doi.org/10.3390/s17061396.
[99] S. Morrone, C. Dimauro, F. Gambella, M.G. Cappai, Industry 4.0 and precision livestock farming (PLF): an up to date overview across animal productions, Sensors-Basel 22 (12) (2022) 4319, https://doi.org/10.3390/s22124319.
[100] S. Abdanan Mehdizadeh, D.P. Neves, M. Tscharke, I.A. Nääs, T.M. Banhazi, Image analysis method to evaluate beak and head motion of broiler chickens during feeding, Comput Electron Agr 114 (2015) 88–95, https://doi.org/10.1016/j.compag.2015.03.017.
[101] D. Tao, Z. Wang, G. Li, G. Qiu, College of Engineering and Technology SUCC, Radon transform-based motion blurred silkworm pupa image restoration, Int. J. Agric. Biol. Eng. 12 (2) (2019) 152–159, https://doi.org/10.25165/j.ijabe.20191202.3681.
[102] R. Vilas Novas, F.L. Usberti, Live Monitoring in Poultry Houses: A Broiler Detection Approach, IEEE, 2017, p. 1.
[103] J. Wang, M. Shen, L. Liu, Y. Xu, C. Okinda, Recognition and classification of broiler droppings based on deep convolutional neural network, J. Sens. (2019) 1–10, https://doi.org/10.1155/2019/3823515.
[104] A. Nasiri, J. Yoder, Y. Zhao, S. Hawkins, M. Prado, H. Gan, Pose estimation-based lameness recognition in broiler using CNN-LSTM network, Comput. Electron. Agric. 197 (2022), 106931, https://doi.org/10.1016/j.compag.2022.106931.
[105] H. Gao, X. Tao, X. Shen, J. Jia, Dynamic scene deblurring with parameter selective sharing and nested skip connections, Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (2019) 3848–3856.
[106] Y. Yao, H. Yu, J. Mu, J. Li, H. Pu, Estimation of the gender ratio of chickens based on computer vision: dataset and exploration, Entropy-Switz. 22 (7) (2020) 719, https://doi.org/10.3390/e22070719.
[107] D. Li, L. Du, Recent advances of deep learning algorithms for aquacultural machine vision systems with emphasis on fish, Artif. Intell. Rev. 55 (5) (2022) 4077–4116, https://doi.org/10.1007/s10462-021-10102-3.
[108] C. Schellewald, A. Stahl, E. Kelasidi, Vision-based pose estimation for autonomous operations in aquacultural fish farms, IFAC-PapersOnLine 54 (16) (2021) 438–443, https://doi.org/10.1016/j.ifacol.2021.10.128.
[109] X. Hu, Y. Liu, Z. Zhao, J. Liu, X. Yang, C. Sun, et al., Real-time detection of uneaten feed pellets in underwater images for aquaculture using an improved YOLO-V4 network, Comput. Electron. Agric. 185 (2021), 106135, https://doi.org/10.1016/j.compag.2021.106135.
[110] S. Kumar, S.K. Singh, R. Singh, A.K. Singh, Recognition of Cattle Using Face Images, Springer Singapore, Singapore, 2018, pp. 79–110.
[111] T. Xue, Y. Qiao, H. Kong, D. Su, S. Pan, K. Rafique, et al., One-Shot Learning-Based animal video segmentation, Ieee T Ind Inform 18 (6) (2022) 3799–3807, https://doi.org/10.1109/TII.2021.3117020.
[112] A.S.M.M. Hasan, F. Sohel, D. Diepeveen, H. Laga, M.G.K. Jones, A survey of deep learning techniques for weed detection from images, Comput. Electron. Agric. 184 (2021), 106067, https://doi.org/10.1016/j.compag.2021.106067.
[113] K. Buddha, J.N. Henry, Z. Dimitris, N. Papanikolopoulos, Weed Detection and Classification in High Altitude Aerial Images for Robot-Based Precision Agriculture. 27th Mediterranean Conference on Control and Automation, MED), 2019.
[114] O. Kupyn, V. Budzan, M. Mykhailych, D. Mishkin, J. Matas, DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018.
[115] C. Hu, B.B. Sapkota, J.A. Thomasson, M.V. Bagavathiannan, Influence of image quality and light consistency on the performance of convolutional neural networks for weed mapping, Remote Sens-Basel. 13 (11) (2021) 2140, https://doi.org/10.3390/rs13112140.
[116] C.S. Nandi, B. Tudu, C. Koley, A machine Vision-Based maturity prediction system for sorting of harvested mangoes, Ieee T Instrum Meas 63 (7) (2014) 1722–1730, https://doi.org/10.1109/TIM.2014.2299527.
[117] C.S. Nandi, B. Tudu, C. Koley, Machine Vision Based Techniques for Automatic Mango Fruit Sorting and Grading Based on Maturity Level and Size Maturity Level and Size, 2013, pp. 27–46, https://doi.org/10.1007/978-3-319-02315-1_2.
[118] C.S. Nandi, B. Tudu, C. Koley, A machine vision technique for grading of harvested mangoes based on maturity and quality, Ieee Sens J 16 (16) (2016) 6387–6396, https://doi.org/10.1109/JSEN.2016.2580221.
[119] G. Hu, E. Zhang, J. Zhou, J. Zhao, Z. Gao, A. Sugirbay, et al., Infield apple detection and grading based on multi-feature fusion, Horticulturae 7 (9) (2021) 276, https://doi.org/10.3390/horticulturae7090276.
[120] O. Mirbod, D. Choi, R. Thomas, L. He, Overcurrent-driven LEDs for consistent image colour and brightness in agricultural machine vision applications, Comput. Electron. Agric. 187 (2021), 106266, https://doi.org/10.1016/j.compag.2021.106266.
[121] W. Yuan, D. Choi, D. Bolkas, P.H. Heinemann, L. He, Sensitivity examination of YOLOv4 regarding test image distortion and training dataset attribute for apple flower bud classification, Int. J. Rem. Sens. 43 (8) (2022) 3106–3130, https://doi.org/10.1080/01431161.2022.2085069.
[122] D. Ochoa, J. Cevallos, G. Vargas, R. Criollo, D. Romero, R. Castro, et al., Hyperspectral imaging system for disease scanning on banana plants (SPIE), Sensing for Agriculture and Food Quality and Safety VIII (2016) 1.
[123] D. Li, R. Wang, C. Xie, L. Liu, J. Zhang, R. Li, et al., A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network, Sensors-Basel. 20 (3) (2020) 578, https://doi.org/10.3390/s20030578.