RESEARCH ON CROP INFORMATION EXTRACTION OF AGRICULTURAL UAV IMAGES BASED ON BLIND IMAGE DEBLURRING TECHNOLOGY AND SVM
/
基于无人机作物图像盲复原及 SVM 的作物信息提取研究

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ABSTRACT
The blurring of crop images acquired by agricultural Unmanned Aerial Vehicle (UAV) due to sudden inputs by operators, atmospheric disturbance, and many other factors will eventually affect the subsequent crop identification, information extraction, and yield estimation. Aiming at the above problems, the new proposed combined deblurring algorithm based on the re-weighted graph total variation (RGTV) and L0-regularized prior, and the other two representative deblurring algorithms were applied to restore blurry crop images acquired during UAV flight, respectively. The restoration performance was measured by subjective vision, and objective evaluation indexes. The crop shape-related and texture-related feature parameters were then extracted, the Support Vector Machine (SVM) classifier with four common kernel functions was implemented for crop classification to realize the purpose of crop information extraction. The deblurring results showed that the proposed algorithm performed better in suppressing the ringing effect and preserving the image fine details, and retained higher objective evaluation indexes than the other two deblurring algorithms. The comparative analysis of different classification kernel functions showed that the Polynomial kernel function with an average recognition rate of 94.83% was most suitable for crop classification and recognition. The research will help in further popularization of crop monitoring based on UAV low-altitude remote sensing.

摘要
由于人为的突然输入，大气扰动以及许多因素将会导致农用无人机获取的作物图像出现模糊现象，最终会影响后续的作物识别，信息提取以及产量估计。针对这个问题，采用一种新提出的基于重加权总变分（RGTV）结合 L0 正则化先验的图像盲复原算法以及其他两种较具有代表性的去模糊算法分别对无人机在作业时获取到的作物图像进行复原处理。采用主观以及客观评价指数对复原效果进行评价。采用带有四种常见核函数的支持向量机分类器用于作物分类从而实现作物信息提取的目的。复原结果表明提出的算法能很好地抑制振铃效应以及保留图像的细节，并有着比另外两种算法较高的客观评价指数上。对不同核函数的分析表明：多项式核函数用于 94.83%的平均识别率是最适合作物的分类以及识别。研究将会帮助采用无人机低空遥感进行作物监测的推广提供一定的帮助。

INTRODUCTION
The rapid acquisition and analysis of crop information are the prerequisite and basis for carrying out precision agricultural practices (*Wang et al., 2014; Lan et al., 2017*). With the development of agricultural remote sensing technology, it has grown up to be an important means of obtaining farmland information in precision agriculture, as well as an important data source for yield estimation, crop type identification, and growth analysis (*Tian et al., 2013; Han et al., 2017*). Recently, agricultural UAV remote sensing platforms, with their characteristics of high timeliness, short operation cycle and high spatial resolution, become a reliable tool of agricultural monitoring (*Chlingaryan et al., 2018*; *Huang et al*., *2018; Garcia et al., 2020*).

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However, the combined influence of atmospheric turbulence, UAV platforms shaking and operation mistakes will make the crop images be blurred and lose valuable information (*Zhang et al., 2012*), which will further affect the yield estimation, crop identification, and other crop-related studies *(Wang et al., 2018*). So far, there are few reports on crop information extraction based on blind image deblurring. Therefore, it is necessary to conduct research on restoration of the blurry crop images obtained during agricultural UAV flight.

Blind image deblurring, a major branch of digital image processing, has been studied extensively and advanced rapidly in remote sensing, text, face, nature, and other types of images in the past decades (*Fergus et al., 2006; Ma et al., 2009; Xu et al., 2017; Pan et al., 2017; Kong et al., 2017; Anger et al., 2019*). Early image deblurring studies mainly focused on the liner motion cases, which exploited parameter estimation methods to obtain the length and angle of the point spread function (PSF) for blind image restoration (*Tiwari et al., 2014*). However, the factors causing image degradation in reality are usually unknown and interactive, which leads to the difficulty of obtaining the PSF parameters (*Li et al., 2019*). In recent years, great progress has been made in blind image restoration algorithms which can be divided into three categories based on the operating principles. The first category is to exploit the regularization techniques to stabilize the restoration process via various priors learned from blur kernels and natural clear images. Then, image deblurring can be achieved by the alternating iterative algorithms (*Shan et al., 2008*). *Krishnan et al. (2011*) propose an image regularization term based on the l1/l2 norm, which can stabilize the kernel estimation process and obtain the satisfactory deblurring results. A simple yet effective L0-regularized prior based on intensity and gradient is adopted to reduce artifacts effectively, which does not require any complex processing techniques (*Pan et al., 2014*). *Pan et al. (2016),* inspired by the dark channel of blurred images that is less sparse, propose a dark channel prior for deblurring text, face, low-illumination and natural images, which does not require heuristic edge selections steps or any complex processing techniques in kernel estimation. *Bai et al. (2018)* design a reweighted graph total variation (RGTV) prior that can efficiently promote a bi-modal edge weight distribution given blurry patch. *Zhu et al. (2019)* apply a nonconvex second-order TV regularization model with linear constraints for remote sensing image restoration, which can preserve the edge information while avoiding the staircase effect. In addition to priors, the second category focus on sharp edge predictions for blur kernel estimation (*Tang et al., 2019*), which are more dependent on the image sharp edges. A combination of knife-edge detection and alternating minimization is applied for blind restoration of remote sensing images (*Shen et al., 2008*), which can stop the iterations at the best visual quality. However, the PSF estimation more relies on the existence of knife-edge features. *Chen et al. (2019)*, inspired by the observation that maximum value of local patch gradient will diminish after the blur process, propose a local maximum gradient prior for blind image deblurring. Chen et al. (2020) propose a novel method based on the non-local self-similarity for blind image deblurring, which can simultaneously capture the intrinsic structure correlation and spatial sparsity of an image. The third category based on deep learning combines neural network with blind image restoration to estimate the blur kernel (*Jidesh et al. 2018; Wang et al. 2018; Li et al., 2019*), which generally requires a lot of training data. Often, the lack of real blurry training data limits the application of this method to some extent.

The Support Vector Machine (SVM), a supervised machine learning technique, have been shown to perform well in non-linear, small sample data, and high-dimensional pattern recognition problems (*Tian et al., 2007*), which has been widely used in crop-related recognition problems as well (*Zhao et al., 2020*). *Li et al. (2012)* apply SVM to recognize wheat stripe rust and wheat leaf rust after segmentation by K-means clustering algorithm, which can successfully discriminate the two. *Li et al. (2020)* prove that the combination of recursive feature elimination algorithm based on SVM (SVM-RFE) feature subset and SVM model have the satisfactory effect on the classification of crops. *Bhatia et al. (2020)* propose a hybrid of Support Vector Machine (SVM) and Logistic Regression (LR) classifier for better prediction of powdery mildew disease in tomato plants.

In this paper, inspired by the idea of the first blind restoration algorithms, the new combined deblurring algorithm based on a more novel and universal RGTV prior and the L0-regularized intensity and gradient prior was proposed to restore blurry millet images obtained by agricultural UAV, and then the research on crop information extraction from the deblurred images with better deblurring performance was conducted. However, when extracting crop-related information, we observed the colour of millet spikes was similar to that of some senile leaves during the mid and late grain-filling stages, which might cause mistakes in crop yield estimation and other related studies.

Their shape-related and texture-related feature parameters with rotation scaling and translation (RST) invariance were extracted. The SVM classifier with different kernel functions was employed for classification to acquire the optimal recognition rate, so as to achieve more accurate crop information extraction.

MATERIALS AND METHODS

Millet images acquisition

The millet images for crop information extraction were obtained by a Phantom4 Advanced UAV at the foxtail millet planting base (millet was planted in late May and harvested in early October) in Zhongyang Village (37°28’ N, 112°39’ E), Taigu District, Shanxi Province, China. The camera was a FC6310 with a resolution of 5472×3648. The crop images were collected in a vertical manner. The UAV flew at a height of 4m with a speed of 3m/s to acquire the crop images on September 27, 2019, from 16:00 to 18:00 in the afternoon. The weather conditions during the period were good. The foxtail millet was in the mid and late grain-filling stages. Figure 1 shows a blurry foxtail millet image obtained during UAV flight.

Fig.1 - A blurry foxtail millet image obtained during UAV flight

The new combined deblurring algorithm based on RGTV prior and L0-regularized prior

The UAV images degradation process may be modeled by a convolution operation:

$$y = k \otimes x + n \tag{1}$$

where y is the observed blurry image, x is the latent sharp image, k is the unknown blur kernel (PSF), and n is random noise which is often modelled as Gaussian. Blind restoration is to recover the latent sharp image x and estimate the blur kernel k only given the blurry image y; the solution of the problem is not only unstable but also non-unique (*Bai et al., 2018*).

To cope with the problem, we present the image RGTV prior combined with the L0-regularized prior blind image restoration algorithm. According to the image degradation model, the maximum a posterior (MAP) framework was exploited to transform the blind image restoration problem into an optimization problem.

$$(\hat{x}, \hat{k}) = \arg\min_{x,k} \{ \frac{1}{2} \|x \otimes k - y\|_2^2 + \lambda \|x\|_{RGTV} + \mu \|k\|_2^2 \} \tag{2}$$

where λ, μ are positive regularization parameters, the first term is the squared L2-norm data-fidelity term. The second term is the regularization term on the latent images, which can efficiently promote bi-modal edge weight distribution of blurry images (*Bai et al., 2018*). The third term is used to regularize the solution of the blur kernel. We optimize (2) by solving the latent image and the blur kernel alternatively. Thus, we divided the problem into x sub-problem:

$$\arg\min_{x} \frac{1}{2} \|x \otimes k - y\|_2^2 + \lambda \|x\|_{RGTV} \tag{3}$$

After a certain number of iterations, not only the more accurate blur kernel is obtained, but we also get an intermediate latent image, which is a gray reconstructed blurry image with robust gradients, yet few details smoothed in the process of estimating the final blur kernel. Therefore, it cannot be regarded as the final restored image. For this reason, the non-blind restoration algorithm based on L0-regularized intensity and gradient prior, which does not require any complex filtering strategies to select salient edges, needs to be exploited to generate satisfactory deblurring performance (*Pan et al., 2014*).

Crop-related information classification using support vector machine

The support vector machine

Support Vector Machine (SVM), proposed by *Vapnik et al. in 1995* (*Vapnik, 2013*), is a supervised classifier. The core idea of SVM is to separate a given set of binary labelled training data with a hyper-plane that is maximally distant from them, which is mainly divided into the linear separable case and the nonlinear separable case (*Hasan et al., 2019*). Here, we focus on the non-linear separable case. To handle nonlinearly separable classes, a nonlinear transformation is used to map the original data points into a higher dimensional space, in which the data points are linearly separable (*Furey et al., 2000*). The corresponding classification decision function is:

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} a_i y_i K(x_i \cdot x) + b\right) \tag{4}$$

where sign( ) is the sign function, a_i is a Lagrange multiplier, b is the threshold of classification, K is the kernel function. Commonly used kernel functions include:

Linear kernel:

$$K(x, x_i) = x^t * x_i \tag{5}$$

Polynomial kernel:

$$K(x, x_i) = \left(x^t * x_i + b\right)^d, b > 0 \tag{6}$$

Radial Basis Function kernel (RBF):

$$K(x, x_i) = \exp\left\{-\frac{|x - x_i|^2}{2\sigma^2}\right\}, \sigma \neq 0 \tag{7}$$

Sigmoid kernel:

$$K(x, x_i) = \tanh\left[\beta x^t x_i + \theta\right] \tag{8}$$

Establishment of SVM classification model

During the mid and late grain-filling stages, we observed that the colour of millet spikes was similar to that of the senile leaves. Directly extracting crop information during UAV flight might confuse, which could cause some mistakes in crop information extraction, yield estimation, and other crop-related researches. In view of the similarity of colour characteristics between millet spikes and senile leaves, the shape-related and texture-related feature parameters with RST invariance were extracted. Among them, the shape-related feature parameters included roundness (C) and Complexity (E); the texture-related feature parameters included Entropy (Ent), Angular Second Moment (Asm), Contrast (Con), and Correlation (Corr). Therefore, the SVM classifier was adopted to distinguish between the crop shape-related and texture-related feature parameters extracted from the millet spikes and leaves, respectively, so as to achieve more accurate information extraction from millet images.

To maximize presentation of the crop features using the extracted information as much as possible, the training samples applied to construct the classification model were taken from clear near-field images (the flying height of UAV was about 2 meters). Firstly, single complete millet spikes and leaves were extracted from the preprocessed crop images by image tool, each of which contained 30 samples. Then, their shape-related and texture-related feature parameters were extracted respectively. The obtained 60 sets of data were applied as inputs of the SVM to identify the best classification model, in which the millet spike samples were labelled as 1, and the leaf samples were labelled as 2. The LIBSVM-FarutoUltimate toolbox was employed to process the extracted feature parameters (Li, 2011). The training samples and the testing samples described in the 3.2 section were normalized by the scaleForClass function. Since the recognition effect of SVM is affected by the kernel function, penalty parameter c, and kernel function parameter g, each parameter of the SVM model was optimized by a grid search using the SVMForClass function, and the five-fold cross validation was used to prevent overfitting in the training process.

RESULTS AND DISCUSSION

The blind image deblurring results

Since the millet images acquired by agricultural UAV contain not only millet, but also weeds and soil, the restoration of the two will not play a significant role in the subsequent millet information extraction. Therefore, a set of blurry crop images was taken out, and the representative image blocks at 482×276 pixels with rich details and as many millet spikes as possible that were intercepted for efficient and fast image processing. We examined our proposed method on three blurry blocks and compared it to state-of-the-art natural image deblurring algorithms which could be detailed in the literature (*Krishnan et al., 2011; Pan et al., 2016*). In addition, in order to better measure the effect of the three deblurring algorithms, the same kernel size for all algorithms was set to estimate the blur kernel in each case. All the experiments were carried out in MATLAB 2017b with an Intel Core i5-6200U processor and 8GB RAM. The experimental results are shown in Figures 2-4, where Figure a represents the blurry image blocks, Figures b and c represent deblurring results based on normalized sparsity prior (*Krishnan et al., 2011*), dark channel prior (*Pan et al., 2016*), respectively. Figure d represents deblurring results restored by the new proposed algorithm.

From Figure 2, it can be seen that the algorithms based on the normalized sparsity prior (Figure (2b)) and the dark channel prior Figure (2c) can obviously restore the crop details, but the deblurring images have a little distortion. The reason leads to the phenomenon that there may be improperly estimated blur kernels, which makes the deblurred result still contain some ringing artifacts and unnatural visual effect. The visual comparisons show that the new proposed algorithm (Figure (2d)) is obviously better than *Krishnan et al. (2011), Pan et al. (2016)*, and can achieve a higher contrast ratio, which will facilitate crop information extraction.

a) Blurry crop image

b) deblurring result of Krishnan et al., 2011

c) deblurring result of Pan et al., 2016

d) deblurring result the new proposed algorithm

Fig. 2 - Comparison of different blind image deblurring algorithms

As shown in Figure. 3, we can see that three deblurring algorithms can better restore the crop details. However, deblurring result based on the normalized sparsity prior Figure (3b), as well as the result based on the dark channel prior Figure (3c), contains obvious ringing artifacts at the edge of the image which decrease the performance of deblurring. As a contrast, the new proposed algorithm Figure (3d) performs better than other compared algorithms in suppressing ringing artifacts of the restored image and can robustly estimate blur kernel. The deblurring result is consistent with the research by *Bai et al. (2018)*.


a) Blurry crop image *b) deblurring result of Krishnan et al., 2011*


c) deblurring result of Pan et al., 2016 *d) deblurring result the new proposed algorithm*

Fig. 3 - Comparison of different blind image deblurring algorithms

As shown in Figure (4c), although a lot of crop details can be recovered, however, there still exists a little blur effect, which may be caused by the inaccuracy of estimated blur kernel. The algorithms based on the normalized sparsity prior Figure (4b) and new proposed algorithm can perform better in visual effect and crop details recovery, but the image restored by the new proposed algorithm Figure (4d) can obtain a clearer blur kernel.


a) Blurry crop image *b) deblurring result of Krishnan et al., 2011*


c) deblurring result of Pan et al., 2016 *d) deblurring result the new proposed algorithm*

Fig. 4 - Comparison of different blind image deblurring algorithms

Apart from the subjective quality assessment, several objective evaluation criteria were also applied to further measure the deblurring performance of the algorithms. Due to the lack of original clear images, we employed three no-reference image quality assessment methods, namely, information entropy, standard deviation, and mean value, which can well measure the amount of information in an image. Generally, the bigger the assessment values, the higher the image quality (*Li et al., 2016*). The calculation results are shown in Tables 1-3.

It can be seen that three evaluation values of the new proposed algorithm are mostly higher than those of the other two algorithms.

At the same time, we can also observe that few values on the proposed algorithm's performance are lower than those of the other two algorithms, which indicates that there may still be some ringing artifacts in the restored images. In short, whether it is from subjective visual effects or objective evaluation indexes, the deblurring algorithm proposed in this paper has better quality than other algorithms.

Table 1

Blind evaluation index without reference quality of Figure 2

Parameter	Information Entropy	Standard deviation	Mean value
Blurred image	7.3245	$1.5852*10^3$	83.8473
Krishnan et al. (2011)	7.5028	$1.9701*10^3$	83.8664
Pan et al. (2016)	7.3850	$2.2949*10^3$	84.1945
Proposed algorithm	7.3808	$2.7058*10^3$	84.7155

Table 2

Blind evaluation index without reference quality of Figure 3

Parameter	Information Entropy	Standard deviation	Mean value
Blurred image	7.1739	$1.4642*10^3$	81.9876
Krishnan et al. (2011)	7.4185	$2.1479*10^3$	81.7898
Pan et al. (2016)	7.2781	$1.8428*10^3$	82.3977
Proposed algorithm	7.4327	$2.4052*10^3$	82.5726

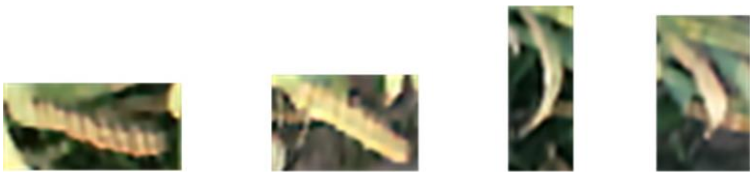
Table 3

Blind evaluation index without reference quality of Figure 4

Parameter	Information Entropy	Standard deviation	Mean value
Blurred image	7.2867	1.7018*103	86.6493
Krishnan et al. (2011)	7.4696	2.9510*103	86.7686
Pan et al. (2016)	7.4506	2.5450*103	87.6612
Proposed algorithm	7.5612	2.5141*103	88.2280

Establishment of SVM test model

The single and complete millet spikes and leaves were intercepted from the deblurred images, each of which contained 12 samples. Two images from each category were displayed in Figure 5. Then, their shape-related and texture-related feature parameters were extracted, respectively. The extracted 24 sets of data were used to establish the SVM testing model, in which the millet spike samples were labelled as 1, and the leaf samples were labelled as 2.



a) millet spike b) millet spike c) senile leaf d) senile leaf

Fig. 5 - The single complete millet spikes and leaves intercepted from the restored crop images

Recognition results of different kernel functions

The SVM with different kernel functions was applied to classify and recognize the millet spikes and leaves samples. The recognition results were shown in Table 4. The results show that the Polynomial kernel function has the best classification performance, and the average recognition rate for the training and testing of these two samples reached 94.83%.

The classification performance of Sigmoid kernel function was second, and the average recognition rate was 93.75%. The classification performance of the Linear kernel function and RBF kernel function was poorer with an average recognition rate of 89.58%. Therefore, the SVM classifier based on Polynomial kernel function was most suitable for distinguishing the millet spikes from the leaves.

Table 4

Results of image recognition of millet spikes and leaves using the SVMs with different kernel functions

Kernel function	Type	Sample		Recognition number		Recognition rate	
		Training sample	Testing sample	Training sample	Testing sample	Training sample	Testing sample
Linear	Millet spikes	30	12	30	10	100%	83.33%
	leaves	30	12	30	9	100%	75%
Polynomial	Millet spikes	30	12	29	10	96%	83.33%
	leaves	30	12	30	12	100%	100%
RBF	Millet spikes	30	12	30	10	100%	83.33%
	leaves	30	12	30	9	100%	75%
Sigmoid	Millet spikes	30	12	30	10	100%	83.33%
	leaves	30	12	30	11	100%	91.67%

As far as we know, crop growth monitoring and yield prediction by agricultural UAV is most commonly performed with the use of RGB (30%) and multispectral (59%) sensors (*Tsouros et al., 2019*), indicating that the implementation of precision agricultural via UAV equipped with RGB sensors has not been spread up so far. Our research about restoration of blurry crop images acquired during UAV flight equipped with RGB sensors and crop-related information extraction has achieved more satisfactory effect, which means that agricultural UAV equipped with RGB sensors for precision agriculture are relatively simple and feasible. This research will help in further promotion of crop monitoring based on UAV low-altitude remote sensing equipped with RGB sensors.

CONCLUSIONS

In this paper, in order to solve the problem that blurry millet images obtained during agricultural UAV flight resulting in the loss of useful information and affect the subsequent crop-related studies, we proposed a new and effective blind image deblurring algorithm based on the image RGTV prior combined with the L0-regularized intensity and gradient prior. Among them, the image RGTV prior, which can promote the bi-modal weight distribution of sharp images from blurry observations, was mainly adopted to obtain the more accurate blur kernel; the L0-regularized intensity and gradient prior was introduced to effectively acquire the final restored image.

The proposed algorithm achieved a highly competitive performance in comparison with other blind restoration methods (*Krishnan et al., 2011; Pan et al., 2016*). When extracting crop-related information from the images restored by proposed algorithm, however, the colour of the millet spikes was similar to that of senile leaves during the mid and late grain-filling stages, which would interfere with crop information extraction. Therefore, their shape-related and texture-related feature parameters with RST invariance were extracted, and the SVM classifier was adopted to distinguish the two.

The results showed that the Polynomial kernel function with an average recognition rate of 94.83% had the best classification performance. The research will provide a reliable basis and approach for realizing information monitoring and crop identification through UAV low altitude remote sensing platforms.

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