Blur Kernel Estimation by Using Bees Algorithm

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***Abstract*— Camera shake is a common source of degradation in digital images taken by an unmanned air vehicle (UAV). Usually, blur kernel is used to reduce the taken image. Blur kernel means the map of camera shake while photo is taken. Estimating an unknown blur kernel from a single input blurred image is a severely ill-posed problem. Blind image deblurring means deblurring with an unknown blur kernel. Blind image deblurring algorithms have been improving continuously in the past years. Most state-of-the-art algorithms still cannot perform perfectly in most cases. In this paper, we focus on how to estimate a good blur kernel from a single blurred image by using Bees Algorithm (BA). We become aware of using BA is a good way to estimate an unknown blur kernel. BA is firstly used for image deblurring in this paper.**

***Index Terms*—Bees Algorithm, BA, blur kernel, blur kernel estimation, blind deblurring.**

I. INTRODUCTION

With the rapid development of image acquisition and processing technology, digital image has been integrated into the modern life. Camera shake is a common source of degradation in digital images taken by an unmanned air vehicle (UAV). Usually, blur kernel is used to reduce the taken image.

Blur kernel means the map of camera shake while photo is taken. The recent years have witnessed significant advances in single image deblurring [1]. Estimating an unknown blur kernel from a single input blurred image is a severely ill-posed problem. Much success of the state-of the-art algorithms [2-8] can be attributed to the use of learned prior from natural images and the selection of salient edges for kernel estimation.

Although numerous methods [2-6] have been proposed for motion deblurring, these priors are not still enough effective. Deblurring with an unknown blur kernel is called blind image deblurring. Blind image deblurring has gained considerable attention and achieved great success in recent years. The formation process of image blur is usually modeled as:

$$B = I * k + n, \quad (1)$$

Where B, I, k and n represent the blurred image, latent image, blur kernel, and the additive noise, respectively. * denotes the convolution operator. It is a well-known ill-posed inverse problem, which requires regularization in order to obtain a high quality latent image. The solution uniqueness cannot be generally guaranteed since the convolution with a blur kernel is noninvertible. To tackle this problem, additional image priors, such as the global gradient distribution from clear images [9], are proposed. Some approaches use multiple images or additional visual cues [10, 11] to constrain the kernel estimation. In this paper we focused on estimating the blur kernel from single image by using Bees Algorithm (BA) [12]. Blur kernel is estimated by the BA and two criteria are used to choose the best kernel. The first criteria is sharpness and the second is blur metric.

II. RELATED WORK

The task of deblurring an image is image deconvolution; if the blur kernel is not known, then the problem is said to be“”blind”. For a survey on the extensive literature in this area, see [13]. While doing the blind image deblurring blur kernel must be found from the blurred image. Camera axis, camera movements and kernel results are shown in the Fig. 1. The camera shake causes a movement on the image like shown in the Fig. 2.

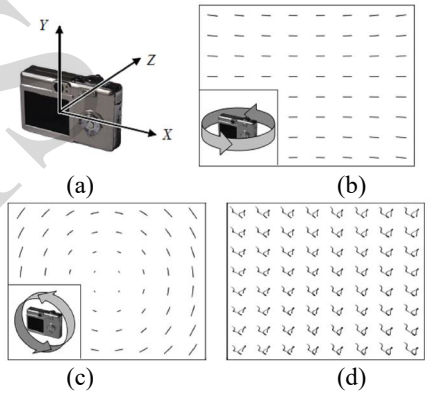


Fig. 1. (a) Angles of the camera, (b) blur kernel of the movement on Y axis, (c) blur kernel of the movement on Z axis, (b) blur kernel of the random movement



Fig. 2. (a) Latent image, (b) blurred image, (c) blur kernel

Fig. 3 shows the overview of our algorithm. Given an observed blurred image, our proposed method iteratively estimates the latent image and refines the blur kernel until convergence. At the beginning the blur kernel is set randomly by BA. Then it is modified by the algorithm at every

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iteration. The error is subtraction of sharpness from blur metric values.

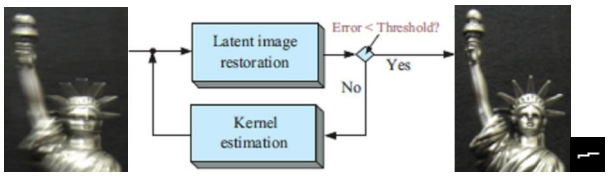


Fig. 3. Overview of algorithm. Given an observed blurred image, our proposed method iteratively estimates the latent image and refines the blur kernel until convergence.

III. BEES ALGORITHM

The BA is inspired by observing the food foraging behavior of the honey bees to obtain the optimal solution to a given optimization problem [12]. A bee colony can be thought of as a distributed creature that can extend itself so as to utilize a large number of food sources at long distances in multiple directions.

The colony tries to attain the most optimal use of colony members by employing more bees for visiting flower areas with more nectar and pollen that can be collected with less effort than the areas with less nectar and pollen. The food search process begins by sending the scout bees from the colony to search for and then evaluate potential flower patches around the hive. A certain percentage of the colony is kept as the scout bees and these scout bees continuously and randomly visit the flower patches around the hive during a harvesting season [14]. The search performed by the scout bees is similar to global search. If a scout bee happen to discover a flower patch that contains more food than a predetermined level, it fly back to the hive and inform the resting nestmates about their finding through a ritual known as the "waggle dance" [12].

This dance allows the other nestmates to accurately evaluate the relative quality of the food areas around the hive and the effort necessary to collect them. After the waggle dance ends, the scout bee flies back to the flower patch together with a number of the resting nestmates. The bee with highest fitness value in each patch is chosen to form the next bee population. This allows the BA to minimise the cost function (CF) given by (2). The search performed by these recruited bees is similar to local search. In this manner, the colony can collect food in a fast and efficient manner. Both global and local search processes provide that the search continues cycle after cycle in an iterative manner until all the good food sources including the best food source in the vicinity of the hive are found. The BA features the same search methods carried out by honey bees in nature.For a survey on the extensive literature in this area; see [12, 15-21].

IV. FORMULATION

Blind image deblurring requires estimation of blur kernel from a single blurred image. The BA is used to estimate the blur kernel by using following cost function formula.

$$CF=BlurMetric-Sharpness \quad (2)$$

Where *CF* is the cost function, *BlurMetric* is the blur value of the image and *Sharpness* is the sharpness of the image.

BlurMetric is calculated by using the algorithm mentioned in [22]. The base of the algorithm is calculation of the blur annoyance on the picture by comparing the variations between neighboring pixels before and after the low-pass filtering step.

Sharpness value is calculated as

$$[Bx, By]=gradient\ (B) \quad (3)$$

$$S=sqrt(Bx^2 +By^2) \quad (4)$$

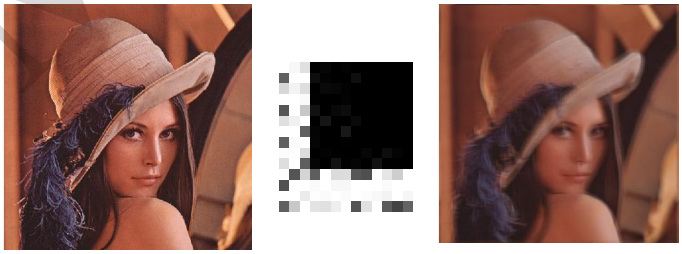
$$sharpness=sum(sum(S))./(numel(Bx)) \quad (5)$$

Where *B* is the blurred image, *numel* is a function that gives the value of number of elements. This is fast and effective way to calculate the sharpness of an image.

In the BA, positions of every bee are a blur kernel. At each iteration, positions of all bees are reduced to find an image which has less BlurMetric and bigger sharpness. At the end of each iteration, all positions are used to deblur the image. The BlurMetric and Sharpness of the resultant images are calculated to find that bee's fitness value. All fitness values are calculated by the formula (2).

V. NUMERICAL RESULTS

To illustrate the capability of the proposed BA for kernel estimation, one kernel estimation example is shown in this paper. The popular Lena picture is used to blur, deblur and kernel estimation problem. Fig. 4 shows the Lena, blur kernel used to blur the Lena and blurred image.



(a) (b) (c)

Fig. 4. (a) The Lena, (b) blur kernel used to blur the Lena (c) blurred image

Fig. 4. (c) Is given as input to the BA. BA starts with random blur kernels. Kernels are used to deconvolution by the blurred image. BA improves the kernels at each iteration to find the best image and best kernel. Fig. 5. shows the results.

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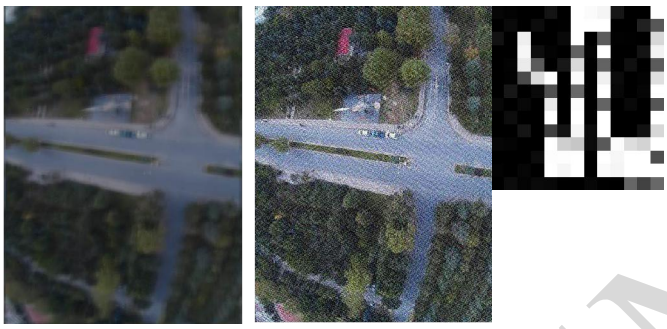


(a) (b) (c)

Fig. 5. (a) Blurred input image, (b) deblurred image (c) computed blur kernel

As shown in the Fig. 5. BA is capable to find best deblurred image and blur kernel.

To illustrate the flexibility of the proposed BA for kernel estimation, one more kernel estimation example is shown in this paper. In this example an unmanned air vehicle (UAV) is used to take the image. The image is blurred because of vibrations on the UAV. Fig. 6. shows the blurred image, deblurred image and computed kernel used to deblur the blurred image.



(a) (b) (c)

Fig. 6. (a) Blurred input image, (b) deblurred image (c) computed blur kernel

VI. CONCLUSION

The degradation of digital images taken by an unmanned air vehicle (UAV) decreases the efficiency of the image. To reduce the effect of vibration on the image some algorithms have been published. In this paper an optimization algorithm called Bees Algorithm (BA) is firstly used to reduce the degradation of digital images and to find the blur kernels. The results show that BA is capable to find the latent image and blur kernel.

ACKNOWLEDGMENT

This work was supported by Research Fund of The Scientific and Technological Research Council of Turkey (TUBITAK) under Project Number: 215M042. The author would like to thank Prof. Dr. M. Emin Yuksel, Ass. Prof. Dr. İlke Turkmen, Ass. Prof. Dr. Tugrul Oktay, Mr. Mehmet Konar and Mr. Hasan Murat Sert for their technical supports during this study and also would like to thank Prof. Dr. Mustafa Kemal Apalak for serving opportunities of Erciyes University, Faculty of Aeronautics and Astronautics.

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