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Recovering Blurred Images to Recognize Field Information †

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Abstract: This paper introduces a new computational approach for fast deblurring non-blind imaging. The method implementation reveals how to solve image deblurring integrals with arbitrary kernels using the Theory of Hypernumbers. The method is applicable for real-time event recognition when kernel parameters can be defined by monitoring camera vibration and kernel–vibration association algorithms.

Keywords: information; image; non-blind; deblurring; hypernumbers

1. Introduction

Information retrieval from images that involves object recognition are now in high demand for many applications [1–6], including military tasks. Using Unmanned Aerial Vehicles equipped with digital cameras for image recording allows us to solve previously unsolved problems. Examples of solving critical problems using this approach include detecting fire sources, locating power lines damage, spotting pipe leaking, finding railroad failures, etc. The image should satisfy some quality requirements in order to allow object recognition. On the other hand, using images recorded from Unmanned Aerial Vehicles is affected by blurring due to the video cameras' random vibration. The main reason of vibration is air turbulence due to strong wind [7]. The level of image blurring depends on the amplitudes of camera displacement due to the vibration. In cases when vibration amplitude would exceed the threshold, the image should be deblurred. Some image recognition applications require real-time recognition and consequently rapid deburring.There are two major directions in image deconvolution: blind and non-blind. The non-blind image deconvolution algorithms recover blurred images with unknown blur kernel. Such methods as Lucy–Richardson [8] and Wiener Filters achieve high resolutions in image deburring. However, it requires hundreds of iterations to obtain original image approximation. The proof of such iterative algorithm convergence is covered in such publications [9]. Non-blind image deburring requires two steps. The first step reveals defining blur kernels, and the second one consists of finding an unknown original image from the blur equation. The first step can be resolved by matching known vibration characteristics to the blur kernel. The second requires solving a non-linear equation. In cases when the kernel is a Gaussian function, it is given constructive formulas for the deblurring of kernels in terms of Hermite polynomials [10].

The numerical solution is defined in [11] for the non-linear diffusion equation is known to be a significant application in solving image processing issues. Per the author's analysis, a largenumber of computations is needed in filtering the image as the sizes keep getting bigger. The authors proposed speeding up the computation in solving the developed linear system with the faster iterative method.

The current research covers the method of deblurring images with arbitrary kernels using the theory of hypernumbers [12,13]. Using hypernumber for solving complex operator equations shows high computational efficiency [14]. The sequential hypernumber

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solution for deblurred images is defined from solving linear equations toward deblurred image variation.

The analysis of the fast deblurring algorithms [15] shows that recovery may take up to minutes. Such speed will not satisfy the real-time processing requirements. The deblurring algorithms are running until the image would be sharpened to a high level.

This method is highly efficient for image processing when time of recovering the image is not critical. For real-time image recognition, we have presented the hypernumber image recovering method.

2. Identifying Original Image by Solving Integral Blurring Equation with Theory of Hypernumber

Per [10], the blurred image can be defined by the following transformation:

$$b^{\delta} = \int\limits_{\Omega} h(s,t)i(t)dt \;\; s \atop i \in \Omega \tag{1}$$

where $h(s,t)$ is the blur kernel, $i(t)$ is the original image, and b^{δ} is blurred image.

In many applications [9], the integral is symmetric convulsion, where kernel is equal to:

$$h(s,t) = h(t,s) = k(s-t) \tag{2}$$

The blurring kernel can be defined with Gaussian distribution [16]:

$$k(s(x,y) - t(u,v)) = e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}} \tag{3}$$

By plugging (3) into (1), the expression for the blurred image is defined as:

$$b^{\delta}(x,y) = \frac{1}{2\pi\sigma^2} \iint\limits_{\Omega} e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}} i(u,v)dudv \tag{4}$$

The area Ω (Figure 1) in the integral is defined to include significant value of the Gaussian function:

$$e^{\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}} < \varepsilon \;\forall\; (x-u) > r \cap (y-v) > r, \tag{5}$$

where ε is significant for blurring value.

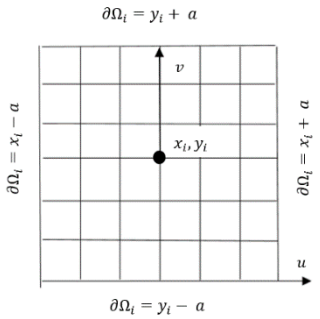

Figure 1. The area of the blurring significance.

Schema from Figure 1 of the calculation of blurring by linear approximation of the delta blurring in area Ω_i

$$\delta b_k(x,y) = \frac{1}{2\pi\sigma^2} \iint\limits_{\Omega} e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}} \delta i_k(u,v)dudv \tag{6}$$

Let:

$$\delta i_{m+1}(x,y\ ) = -\mu\Big(b_m^{\delta}(x,y) - b^{\delta}(x,y)\Big) \tag{7}$$

The image hypernumber is defined as:

$$i_m = H_n(i_m)_{m\in w} \tag{8}$$

$$i_{m+1} = i_m + \delta i_{m+1} \tag{9}$$

$$\delta b_{m+1}^{\delta}(x,y) = \frac{-\mu}{2\pi\sigma^2}\iint\limits_{\Omega}\Big(b_m^{\delta}(u,v) - b^{\delta}(u,v)\Big)e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}}dudv \tag{10}$$

$$b_{m+1}^{\delta}(x,y) = b_m^{\delta}(x,y) + \delta b_{m+1}^{\delta}(x,y) \tag{11}$$

The hypernumber solution should satisfy the difference between the blurred image with image hypernumber and the original blurred image to be equal to zero.

$$\begin{gathered} b_{m+1}^{\delta}(x,y) - b^{\delta}(x,y) = b_m^{\delta}(x,y) - b^{\delta}(x,y) - \\ \frac{\mu}{2\pi\sigma^2}\iint\limits_{\Omega}\big(b_m^{\delta}(u,v) - b^{\delta}(u,v)\big)e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}}dudv \end{gathered} \tag{12}$$

Let:

$$b_m^{\delta}(u,v) - b^{\delta}(u,v) = \Big(b_m^{\delta}(x,y) - b^{\delta}(x,y)\Big) + \Delta b_m^{\delta}\ (u,v) \tag{13}$$

and

$$\Big|\Delta b_m^{\delta}\ (u,v)\Big| < \Delta_m \tag{14}$$

Then, plugging (12) into (11) and using (13), we obtain such inequality $\beta = \frac{\mu}{2\pi\sigma^2}$

$$\begin{gathered} \big|b_{m+1}^{\delta}(x,y) - b^{\delta}(x,y)\big| \leq \\ \left|\big(\ b_m^{\delta}(x,y) - b^{\delta}(x,y)\big)(1-\beta) + \beta\Delta_m\iint\limits_{\Omega}e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}}dudv\right| \end{gathered} \tag{15}$$

Since the integral over Gaussian kernel equals to 1:

$$\iint\limits_{\Omega}e^{-\frac{(x-u)^2+(y-v)^2}{2\pi\sigma^2}}dudv = 1 \tag{16}$$

Equation (15) can be re-written:

$$\Big|b_{m+1}^{\delta}(x,y) - b^{\delta}(x,y)\Big| \ \leq\ \Big|\Big(b_m^{\delta}(x,y) - b^{\delta}(x,y)\Big)(1-\beta) + \beta\Delta_m\Big| \tag{17}$$

The defined algorithm of constructing the hypernumber solution provides a computanional mechanism of $|\Delta_m| < \frac{\left|b_m^{\delta}(x,y) - b^{\delta}(x,y)\right|}{k}$, $k > 1$ and consequently $\left|b_{m+1}^{\delta}(x,y) - b^{\delta}(x,y)\right| < \frac{\left|b_m^{\delta}(x,y) - b^{\delta}(x,y)\right|}{l}$, l >1.

3. Conclusions

The software implementation of the approach defined in this paper shows the efficiency in deblurring the image with Gaussian kernel. The image recovering time is less than one second.

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References

1. Cazzato, D.; Cimarelli, C.; Sanchez-Lopez, J.L.; Voos, H.; Leo, M. A Survey of Computer Vision Methods for 2D Object Detection from Unmanned Aerial Vehicles. *J. Imaging* **2020**, *6*, 78. [CrossRef] [PubMed]
2. Cerón, A.; Mondragón, I.; Prieto, F. Onboard visual-based navigation system for power line following with UAV. *Int. J. Adv. Robot. Syst.* **2018**, *15*. [CrossRef]
3. Oleshko, T.; Kvashuk, D.; Heiets, I. Image recognition in unmanned aviation using modern programming languages. *SN Appl. Sci.* **2019**, *1*, 1–10. [CrossRef]
4. Rubio, V.; Ferran, J.; Garcia, J.; Almodovar, N.; Mayordomo, J.; Alvarez, V. Automatic Change Detection System over Unmanned Aerial Vehicle Video Sequences Based on Convolutional Neural Networks. *Sensors* **2019**, *19*, 4484. [CrossRef] [PubMed]
5. Matikainen, L.; Lehtomäki, M.; Ahokas, E.; Hyyppä, J.; Karjalainen, M.; Jaakkola, A.; Kukko, A.; Heinonen, T. Remote sensing methods for power line corridor surveys. *ISPRS J. Photogramm. Remote Sens.* **2016**, *119*, 10–31. [CrossRef]
6. Zohair, A.; Dzulkifli, M.; MohdSharfy, M.R.; Ghazali, S. Restoring Degrade Astronomy Images using a Combination of Denoising and Deblurring Techniques. *Int. J. Signal Process. Image Process. Pattern Recognit.* **2012**, *5*, 1–11.
7. Sieberth, T.; Wackrow, R.; Chandler, J.H. UAV Image Blur—Its Influence and Ways to Correct it. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-1/W4. In Proceedings of the 2015 International Conference on Unmanned Aerial Vehicles in Geomatics, Toronto, TN, Canada, 30 August–2 September 2015; Available online: https://www.int-arch-photogramm-remote-sens-spatial-inf-sci.net/XL-1-W4/33/2015/isprsarchives-XL-1-W4-33-2015.pdf (accessed on 19 October 2015).
8. Tai, Y.; Tan, P.; Brown, M.S. Richardson-Lucy Deblurring for Scenes under a Projective Motion Path. *IEEE Trans. Pattern Anal. Mach. Intell.* **2011**, *33*, 1603–1618. [CrossRef] [PubMed]
9. Khan, M.; Morigi, S.; Reichel, I.; Sgallari, F. Iterative Methods of Richardson-Lucy type for Image Deblurring. *Numer. Math. Theor. Meth. Appl.* **2013**, *6*, 262–275. [CrossRef]
10. Hummel, R.; Kimia, B.; Zusker, S. *Deblurring Gausian Blur. Robotics Report No. 23*; New York University: New York, NY, USA, 1986.
11. A Basran, N.; Eng, J.H.; Saudi, A.; Sulaiman, J. Numerical Solution of Non-Linear Diffusion Equation in Image Blurring Using Two-Point EGSOR Iterative Method. *J. Physics: Conf. Ser.* **2019**, *1358*, 012050. [CrossRef]
12. Burgin, M. Nonlinear Partial Differential Equations in Extrafunctions. *Integr. Math. Theory Appl.* **2010**, *2*, 17–50.
13. Burgin, M.; Dantsker, A.M. A method of solving operator equations by means of the theory of hypernumbers. *Not. Nat. Acad. Sci. Ukr.* **1995**, *8*, 27–30. (In Russian)
14. Burgin, M.; Dantsker, A.M. *Real-Time Inverse Modeling of Control Systems Using Hypernumbers*; Functional Analysis and Probability, Nova Science Publishers: New York, NY, USA, 2015; pp. 439–456.
15. Hirsch, M.; Schuler, C.J.; Harmeling, S.; Scholkopf, B. Fast removal of non-uniform camera shake. In Proceedings of the 2011 International Conference on Computer Vision, Washington, DC, USA, 6–13 November 2011.
16. Hossain, F.A.; Zhang, Y.M.; Tonima, M.A. Forest fire flame and smoke detection from UAV-captured images using fire-specific color features and multi-color space local binary pattern. *J. Unmanned Veh. Syst.* **2020**, *8*, 285–309. [CrossRef]