

PAPER • OPEN ACCESS

A process for the accurate reconstruction of pre-filtered and compressed digital aerial images

To cite this article: Gabriel Scarmana and Kevin MacDougall 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **509** 012047

View the [article online](#) for updates and enhancements.

A process for the accurate reconstruction of pre-filtered and compressed digital aerial images

Gabriel Scarmana and Kevin MacDougall

School of Civil Engineering and Surveying,
University of Southern Queensland, Australia

gabriel.scarmana@usq.edu.au, kevin.mcdougall@usq.edu.au.

Abstract. The study of compression and decompression methods is crucial for storage and/or transmission of large numbers of image data which is required for archiving aerial photographs, satellite images and digital ortho-photos. Hence, the proposed work aims to increment the compression ratio (CR) of digital images in general. While emphasis is made on aerial images, the same principle may find applications to other types of raster based images.

The process described here involves the application of pre-defined low-pass filters (i.e. kernels) prior to applying standard image compression encoders. Low-pass filters have the effect of increasing the dependence between neighbouring pixels which can be used to improve the CR. However, for this pre-filtering process to be considered as a compression instrument, it should allow for the original image to be accurately restored from its filtered counterpart.

The development of the restoration process presented in this study is based on the theory of least squares and assumes the knowledge of the filtered image and the low-pass filter applied to the original image. The process is a variant of a super-resolution algorithm previously described, but its application and adaptation to the filtering and restoration of images, in this case (but not exclusively) aerial imagery, using a number of scales and filter dimensions is the expansion detailed here. An example of the proposed process is detailed in the ensuing sections. The example is also indicative of the degree of accuracy that can be attained upon applying this process to gray-scale images of different entropies and coded in a lossy or lossless mode.

Introduction

In this contribution a method is suggested whereby the CR of a given image can be significantly improved. The process is based on reducing the image entropy by means of low-pass filters prior to applying standard compression protocols [1]. The filtered image is then thoroughly restored by inverting the filtering process. In this context, low-pass filters (i.e. linear kernels) are investigated so as to determine the influence they have on the CR and how they can be used to reverse the filtering effect and thereby inherently restore the original image. Clearly, pre-filtering is usually treated as an operation to remove noise [1]. But here pre-filtering is considered more in the sense of pre-blurring for compression processes [2].

The restoration process described here implies the knowledge of the filtered image (i.e. the blurred image) and the kernel used to filter it. The kernel serves as a way of letting the process recognize what type of filtering or degradation it should reverse. The general idea emerges from the theory of linear least squares as applied to super-resolution image enhancement process originally published in [3] and provides for an alternative to state of the art restoration procedures such as neural networks [4].



1. How does it work? – the principle

The proposed process is based on a linear algebraic approach. Referring to Figure 1, the 3x3 kernel K (an approximate Gaussian filter) is used to blur image P. The result of this filtering process is given in image C. The pixels of C (83, 84, 55...etc.) are computed from the set of observation equations also given in Figure 1:

256	100	80	P
30	40	160	
10	90	200	

1	2	1	K
2	4	2	
1	2	1	

$$\frac{1}{16} \begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix}$$

83	84	55	C
58	92	92	
66	84	20	

$$83 = (4p_1 + 2p_2 + 2p_4 + p_5) / 16$$

$$84 = (2p_1 + 4p_2 + 2p_3 + p_4 + 2p_5 + p_6) / 16$$

$$55 = (2p_2 + 4p_3 + p_5 + 2p_6) / 16$$

$$58 = (2p_1 + p_2 + 4p_4 + 2p_5 + 2p_7 + p_8) / 16$$

$$92 = (p_1 + 2p_2 + p_3 + 2p_4 + 4p_5 + 2p_6 + p_7 + 2p_8 + p_9) / 16$$

$$92 = (p_2 + 2p_3 + 2p_5 + 4p_6 + p_8 + 2p_9) / 16$$

$$66 = (p_4 + 2p_5 + p_6 + 2p_7 + 4p_8 + 2p_9) / 16$$

$$84 = (p_5 + 2p_6 + 2p_8 + 4p_9) / 16$$

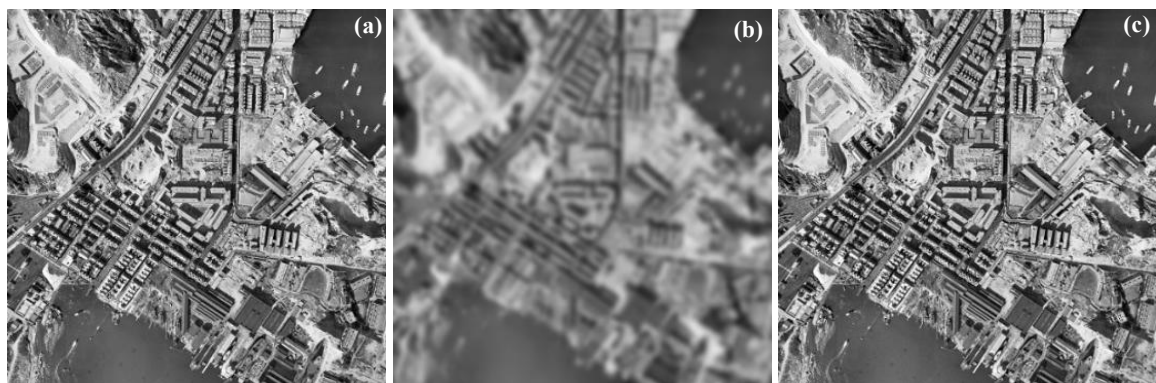
$$20 = (2p_4 + p_5 + 4p_7 + 2p_8) / 16$$

Figure 1. The original image P is multiplied (or convoluted) using a normalised kernel K. The result of the convolution is image C on the right together with the equations used to calculate image C.

The above set of observation equations can also be used in reverse so as restore, by way of least squares, the pixels of the original image P. Due to the nature of least squares theory and due to the fact that the pixels in C are rounded to the nearest integer, a perfect restoration of P may not always be attained. In this simplistic example the RMSE [5] of the differences between image P and image C was +/- 1.8 grey intensity values (grey scale ranging between 1-256).

2. Example

The image (a) below (1000², 1 MB, entropy = 6.9) was .PNG compressed [6] resulting in a storage requirement of 0.5 MB. To process image (a) using the 3x3 low-pass filter [1 2 1, 2 4 2, 1 2 1]/16 and obtain image (b) took 3 seconds. However, reversing the process and obtain image (c) (i.e. the restored image), which required the solution of a system of equation of 2500 unknowns (50² original pixels per block of 50² pixels) needed 4 seconds. This implies an asymmetric restoration process. The RMSE of the difference between image (a) and image (c) was +/-3.3 pixel intensity values with a max. and min. differences of -4 and +5 pixel intensity values.



References

- [1] Rahman M.A., Lin S. C. F., Wong C. Y., Jiang G., Liu S. and Kwok N. 2016. Efficient colour image compression using a fusion approach. *The Imaging Science Journal* Vol. 6, Iss. 3.
- [2] Showengerdt R. A. 2007. *Remote Sensing: Models and Methods for Image Processing*. Elsevier.
- [3] Katsaggelos K. A. 2012. *Digital Image Restoration*. Springer Publishing Company Inc.
- [4] Bahadir K. G., Xin Li. 2012. *Image Restoration: Fundamentals and Advances*. Digital Imaging and Computer Vision. 1st Edition. 378 pages. CRC Press. Taylor and Francis.
- [5] R. Gonzalez and R. Woods. 2018. *Digital Image Processing*, 4th ed. Pearson Publisher. 1192 pages.
- [6] Scarmana G. 2014. Lossless data compression of grid-based digital elevation models: A PNG image format evaluation. *ISPRS. Annals of Photogrammetry and Remote Sensing*, isprsannals-II-5-313.