IOP Conference Series: Earth and Environmental Science

PAPER • OPEN ACCESS

Digital image improvement by integrating mages of different resolutions

To cite this article: Gabriel Scarmana 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **509** 012046

IOP Conf. Series: Earth and Environmental Science **509** (2020) 012046 doi:10.1088/1755-1315/509/1/012046

Digital image improvement by integrating mages of different resolutions

Gabriel Scarmana

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

gabriel.scarmana@usq.edu.au

Abstract. This proof of concept paper evaluates the performance of super-resolution (SR) imaging when combining a sequence of images of different resolutions. Traditional work in SR requires accurate sub-pixel registration and/or alignment techniques. The assumption is that all the frames in the sequence are captured with a random sub-pixel translation and at the same spatial resolution. However, if there is no relative motion between the scene and the sensor, the super-resolution problem can be approached by integrating images of different resolutions using the image re-sampling ratios as the enhancing factor. This may be the case of using digital zooms whereby a scene of interest is enhanced by integrating the information obtained from capturing said scene at different zoom levels.

Preliminary results of conducting tests on synthetic and real data (scanned images) are presented. In both cases the process under-samples the image of an object of interest within a scene at different resolutions. By integrating these images using an algebraic process an improved composite is obtained containing more spatial information than that provided by simply interpolating on a single image.

Introduction

HR images depend on sensor manufacturing technology which tries to increase the amount of pixels per unit area by reducing the pixel size. However, the cost for high-precision optics and sensors may be unsuited in some applications. In addition, there exist several optical restrictions on the pixel size that makes it unwise to further reduce the pixel size beyond those restrictions [1]. A foremost limitation of reducing the pixel size is that pixel sensitivity is significantly reduced as the pixel size is reduced [2].

Therefore, images acquired through such sensors suffer from different degrees of aliasing and blurring. Aliasing occurs as a consequence of insufficient density of the detector array which causes sampling of the scene at less than the Nyquist rate, while blurring occurs due to integration of the sensor point spread function (PSF) at the sensor surface. Hence, image processing methods such as SR are considered to construct a high-resolution image from one or more available low-resolution images of the same scene [3].

Usually, SR is applicable if vibration of the sensor setup (i.e. camera) causes a random, sub-pixel, global translation of the scene before sampling. In addition, the low-resolution images to be used in the enhancement process are of the same spatial resolution [4]. On the other hand, in the event of the image sensor being static (i.e. fixed surveillance video cameras) the low-resolution images required for the enhancement may be obtained from the different views of the region or image section of interest taken at different resolutions such as in the case, for example, of using digital zooms.

Digital zooms were a marketing point in the early days of digital cameras, but over time, camera makers focused less and less on this specification. However, due to the advent of smart phones digital zooms are making a solid comeback. This is because smart phones cannot physically accommodate an optical zoom lens construction and/or architecture.

By varying the zoom level, it is possible to observe and/or capture images of the same scene of interest at different levels of aliasing and blurring. These images may then be integrated or mapped within a common framework and thereby obtain a desired higher resolution composite.

For this reason, in this paper a new approach is presented which generates a super-resolved image using the zoom level as the enhancing factor. The resolution at which the most zoomed area of interest is available is the resolution to which the entire scene needs to be super-resolved. This requires the recovering and mapping on a common higher resolution grid the coarse (i.e. unprocessed) intensity values for the lesser zoomed areas of the scene of interest. In other words, only a part of the observed zoomed image has multiple observations, that is, the most zoomed scene. Figure 1, graphically describes the above concepts.

1. Results

An example of the effectiveness of this algorithm is seen in Figure 1, which represents the general two-dimensional case. A sequence of 5 low-resolution images of the original *lighthouse* (120^2) was simulated by down-sampling said original images by the following factors: 2, 3, 4, 6 and 9. This process generated five .png images of the *lighthouse* having the following resolutions: 85^2, 70^2, 60^2, 50^2 and 40^2 pixels. Only three of these multi-resolution images (i.e. 85^2, 60^2 and 40^2) are shown below together with the final enhanced composite 3(d). Note how simple averaging merely produces a blurred image with less contrast and fine details as shown in Figure 3(e).

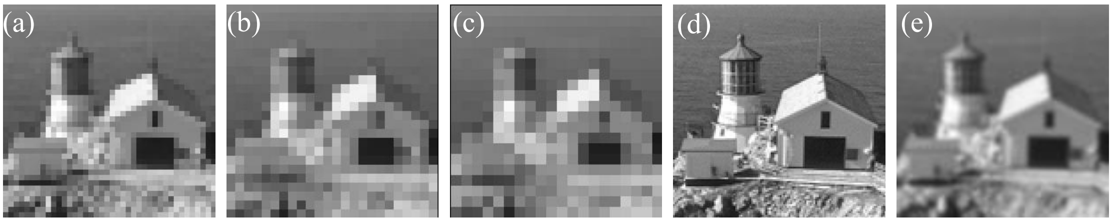

Figure 1. Three of the five coarse images (a-c), the resolution enhanced composite (d), simple averaged image (e). The averaged image is based on up-sampling image (a).

At present the reduction ratios, or factors amongst the input images must be known. Hence, future work will investigate the possibility of automatically finding the difference in scale between each image or solve for it in the solution automatically.

Real time applications of the proposed process such as those using mobile phones will also require the automatic and simultaneous computation of relative sub-pixel shifts between the set of multi-resolution images. It is envisaged that this may be achieved by performing the matching in a pyramid manner whereby the low-resolution images are registered or matched in succession. For instance, and referring to Figure 1, image (c) would be first matched/registered to image (b) and image (b) would be matched with image (a).

References

[1] R.A. Schowengerdt. 2007 Remote Sensing: Models and Methods for Image Processing. Elsevier. 515 pages.

[2] R. Gonzalez and R. Woods. 2018 Digital Image Processing. 4th edition, Pearson Publisher.

[3] A. K. Nasrollahi and T. B. Moeslund. 2014. Super-resolution: A comprehensive survey. Machine Vision & Applications **Vol. 26**, Issue 6. pp 1423-1468.

[4] S. Baker and Kanade T. 2002 Limits on Super-Resolution and How to Break Them. IEEE. Transactions on Pattern Analysis and Machine Intelligence. **Vol. 24**. Issue 9.