Image Subsampling Strategies for Energy-Efficient Computer Vision

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***Abstract*—One recent trend in industry is to enable embedded and mobile platforms to be energy-efficient with longer battery lives. For machines performing a computer vision task with a camera, a principal mechanism to conserve energy is to subsample captured images to lower resolution. In this paper, we investigate a different manner of image subsampling that does not sacrifice accuracy of a computer vision task being performed. Through our experimentation, we propose using a heuristic algorithm to determine the most energy-efficient subsampling for a given task.**

I. Introduction

For devices performing a computer vision task, energy is consumed when a camera captures all the pixels of an image. In addition, additional energy, time, and memory is consumed when these images are processed depending on the size of image. By proposing a novel manner of image subsampling, we seek to increase energy efficiency for such devices by allowing them to not capture all the pixels of an image.

Normal image sensors perform uniform spatial sampling of a scene in order to produce an image. The most common method to increase the efficiency of processing these images is to uniformly subsample the image by downsampling the dimensions. But while this might save time and energy processing the image, this re-sizing may introduce blur and/or noise which may hinder the accuracy of a computer vision task.

Fig. 1. Comparing two methods of image subsampling on the original image. The middle image demonstrates scaling, an example of uniform image subsampling. The right image consists of randomly selected of pixels that been removed, an example of non-uniform image subsampling.

Uniform image subsampling uses global information when determining what information should be removed from the image. Non-uniform image subsampling, in contrast, can be spatially localized or even context-dependent, and thus may preserve details and features necessary for computer vision while still reducing the number of pixels. As Figure 1 demonstrates, an example of non-uniform image subsampling is randomly removing a set of pixels from an image.

In particular, image subsampling that does not require all the pixels of an image demonstrates promise when applied to self-powered cameras that are utilized to perform a computer vision task. Self-powered cameras convert light energy into electrical energy, but this energy is consumed when a photodiode measures the light intensity to produce a pixel of an image [1]. Hence, by capturing an image with a removed set of pixels, the camera will harvest more energy for every pixel that is not captured.

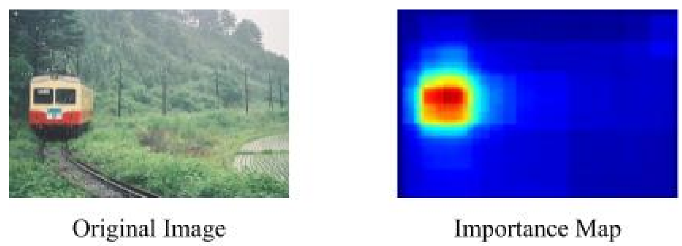

Fig. 2. Object analysis that produces an importance map of an image. This object analysis will be utilized as proxy to determine the accuracies of a computer vision task between the original and subsampled images.

In this paper, we investigate various patterns of uniform and non-uniform image subsampling to determine the most energy-efficient method. Comparing the object analysis between the original and sub-sampled image [2, 3] as Figure 2 depicts, we utilize this objectness as a proxy to determine the accuracy of a computer vision task and show this with three applications: object detection [4], classification [5], and segmentation [5]. Using this objectness measure, we then develop a heuristic algorithm to determine the most energy-efficient image subsampling patterns.

References

[1] S. K. Nayar *et al.*, "Towards self-powered cameras," in *Computational Photography (ICCP), 2015*. IEEE, 2015, pp. 1–10.

[2] B. Alexe, T. Deselaers, and V. Ferrari, "What is an object?" in *CVPR, 2010 IEEE Conference on*. IEEE, 2010, pp. 73–80.

[3] B. Alexe *et al.*, "Measuring the objectness of image windows," *IEEE trans. on pattern analysis and machine intelligence*, vol. 34, no. 11, pp. 2189–2202, 2012.

[4] S. Ren *et al.*, "Faster r-cnn: Towards real-time object detection with region proposal networks," in *Adv. in neural info. proc. systems*, 2015, pp. 91–99.

[5] A. Vedaldi *et al.*, "Matconvnet: Convolutional neural networks for matlab," in *Proc. of the 23rd ACM international conf. on Multimedia*. ACM, 2015, pp. 689–692.