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Trading sharpness with energy consumption in a lens autofocus application

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Abstract—Approximate computing is an emerging paradigm in which the accuracy of computation results can be traded against, e.g., savings in energy, improvement in performance. In this extended abstract we investigate, by means of an example, the applicability of approximate operators (additions, in our case) on an adaptive feedback control loop. Our research vehicle is a autofocus controller that sets the focal distance of a lens such that a defined region of interest (ROI) in the output image is sharp. We study the energy consumption and the ROI sharpness error for various operation approximation degree. The results are encouraging indicating that for a 30% reduction on the energy consumed in the addition operations the degradation in the sharpness of only 2%. A 40% reduction on the energy consumed corresponds to a less than 10% degradation.

I. INTRODUCTION

Low power consumption is a crucial challenge in embedded devices that are battery powered or that need to harvest their energy. The approximate computing paradigm [1], [2] aims to respond to this challenge by trading accuracy of computation against savings in energy, for algorithms that tolerate a bounded error in operations (e.g., addition, multiplication) or operands (e.g., registers, memory). Typical targets where this paradigm may bring significant benefits are signal processing, machine learning, multimedia, iterative algorithms.

In this work we investigate the trade-off between energy and output quality in an application comprising an adaptive feedback control. The use-case application is an autofocus system in charge of controlling the focal distance of a lens such that a defined region of interest (ROI) in the output image is sharp. Hence, in our case the quality metric is ROI sharpness. The autofocus system includes a simple, adaptive integral controller and a Haar wavelet and an ℓ_1 norm to compute the sharpness. We compare two ways of employing approximate operations in the sharpness computation: (1) in the Haar wavelet and the ℓ_1 norm and (2) in the Haar wavelet. The practical experimentation platform is an Raspberry-Pi board and a Microelectromechanical (MEM) based lens.

II. AUTOFOCUS USE-CASE AND RESULTS

A. Target application

The lens autofocus system, as proposed in [3], consists of a control loop that aims to maximise a sharpness metric. Figure 1 briefly presents this control loop. At each control step, an image is taken, the region of interest (ROI) is extracted and a sharpness metric, s , and its gradient are calculated. Based on the sharpness gradient the adaptive controller decides how to update its gain and computes the control signal, c , (a voltage in our case), so that an image with a different focal distance is taken on the next step. The process stops when the sharpness gradient is smaller than a given reference or a predefined

number of steps is reached. The control signal belongs to a set of discrete values; for simplicity, in what follows we report it as normalised with respect to a maximum value.

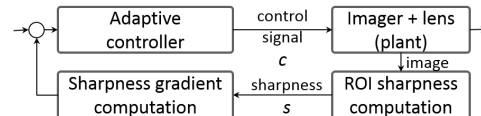


Fig. 1. Autofocus control loop

Most of the execution time in the control loop is spent on the sharpness computation, hence our investigation focuses on this part of the application. The sharpness metric includes two main kernels: a Haar wavelet and a ℓ_1 norm. Most of the operation involved in the sharpness computation are additions. The algorithm below presents the details of the calculation.

Require: $imageROI, nRow, nCol, order$ {2D matrix with the ROI pixel values, number of rows and columns of ROI, Haar wavelet order}

Ensure: s {the sharpness}

$s \leftarrow 0$

$hout \leftarrow imageROI$

$vout \leftarrow imageROI$

for i in $[1, order+1]$ **do**

$hout \leftarrow hout[:, 1 : nCol : 2] - hout[:, 0 : nCol - 1 : 2]$

$hout \leftarrow hout[1 : nRow : 2, :] + hout[0 : nRow - 1 : 2, :]$

$vout \leftarrow vout[:, 1 : nCol : 2] + vout[:, 0 : nCol - 1 : 2]$

$vout \leftarrow vout[1 : nRow : 2, :] - vout[0 : nRow - 1 : 2, :]$

$s \leftarrow s + \frac{\sum |hout| + \sum |vout|}{768 * 2^i}$ { ℓ_1 norm}

end for

return s

To evaluate the impact of approximate additions on the quality of application results, we define the relative sharpness error, rse , for an image as:

$$rse = \left| \frac{s_{ref} - s_a}{s_{ref}} \right|, \quad (1)$$

where s_a is the sharpness in the approximate case, and s_{ref} is the reference sharpness. For a given image, Figure 2 presents the sharpness versus control signal plot for a real image example, and illustrates the values involved in the determination of the error metric. In the case that the operations are approximate, the control loop will converge towards a different value of the control signal, c_a . As a result, the image sharpness will have a value denoted as s_a . To define a maximum sharpness reference s_{ref} , we take an intermediate step, because the output of the image sensor is inherently noisy. A sharpness curve is interpolated using B-spline from a set of sharpness of images corresponding to all possible

focal distances (i.e., values of control signals). The maximum sharpness point s_{ref} is the maximum of this curve.

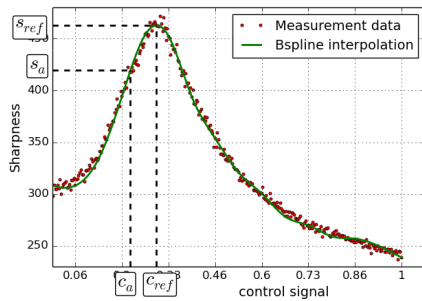


Fig. 2. Error metric example

B. Energy and error model

We utilise a simple error model for the addition operations, as follows: $(x + y)_a = (x + y)_e * (1 + \epsilon)$, where $\epsilon \in [-1, 1]$ represents the relative error of an approximate adder and the a and e indices denote an approximate and an exact operation, respectively. We consider that the energy consumption of an exact addition equals 1 unit, similar with [4]. An approximate operation typically consumes a fraction of this unit of energy, denoted with e_a , $e_a < 1$. We assume that ϵ follows a Laplace distribution, as empirically observed in previous work on modeling approximate adders [5]. For a given e_a we utilise the results of Kahng and Kang, [6] to determine the mean and scale of the relative error distribution for a given level of energy, e_a . The Laplace distribution is utilised to inject errors in the sharpness computations. For a given number of approximate operations, n_a and exact operations, n_e , the total normalised energy is given by: $E = \frac{n_a * e_a + n_e * 1}{(n_a + n_e)}$

C. Experimental results

The experimental platform used to acquire all images, embeds an imager, a lens and a Raspberry Pi board that implements the autofocus algorithm, as presented in Figure 3. We consider a ROI with 256x256 pixels, which corresponds to 17K addition operations necessary to compute the sharpness.



Fig. 3. Demonstration platform

We investigate two cases: (1) all additions, in the Haar wavelet and the ℓ_1 norm, are approximate, (2) additions in the Haar wavelet are approximate and the ℓ_1 norm is precise. The baseline is the precise sharpness computation using exact additions. Note that, due to noise in the images, the relative sharpness error of the baseline is not always zero. Figure 4

summarises the results, for several values of the energy level, e_a . The results indicate that for a 30% reduction on the energy consumed in the addition operations the degradation in the sharpness is only 2%. A 40% reduction on the energy consumed corresponds to a less than 10% degradation.

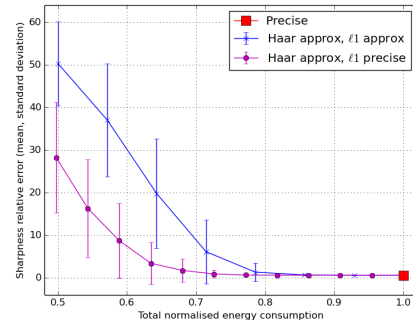


Fig. 4. Energy vs sharpness (comparison between the two cases)

III. CONCLUSION AND PERSPECTIVES

This work investigates the applicability of the approximate computing techniques on a lens autofocus system. The study indicates a significant energy gain potential for a small loss in final image sharpness.

It is worth noticing that feedback control algorithms rarely benefit from approximate operations because the errors introduced may render a controller unstable. In this sense this work extends on the state-of-the-art by investigating the applicability of approximate operators on an adaptive feedback control loop. The particularity of this loop is that it takes decisions based on the output gradient and not directly on the output. Even if the output is imprecise, its gradient may still be in the correct direction, hence the loop has the potential to tolerate the approximations in the operators. A theoretical framework to reason about stability in the presence of approximate operators is an interesting research direction. Other limitations to be addressed in future work are: (1) the error probability vs. energy model is a compilation from literature, hence it might be unrealistic, and (2) the energy model is oversimplistic as it abstracts from the consumption on parts of a processor, such as, instruction decoding, memory access.

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