Neuro-inspired Image Compression Architectures

Anastasios Papanastasiou
Technical University of Crete
Chania, Greece
apapanastasiou1@isc.tuc.gr

Effrosyni Doutsi
Technical University of Crete,
Foundation for Research and
Technology – Hellas
Heraklion, Greece
edoutsi@ics.forth.gr

Michalis Zervakis
Technical University of Crete,
Chania, Greece
mzervakis@isc.tuc.gr

Panagiotis Tsakalides
University of Crete
Foundation for Research and
Technology – Hellas
Heraklion, Greece
Tsakalid@ics.forth.gr

***Abstract* — The goal of this work is to propose an end-to-end image compression architecture that consists of a well-known transform, like the Discrete Cosine Transform (DCT) or the Discrete Wavelet Transform (DWT), and the recently released neuro-inspired quantization that is based on the Leaky Integrate-and-Fire neuron. This novel quantization mimics the visual system that can be seen as an intelligent biological "machine" that is able to capture and transform the visual stimulus into a sequence of discrete events, called spikes. This spike train is informative enough for the human brain to perceive and take decisions according to the content of the visual stimulus. As a result, it is expected that mimicking the way the neurons generate this code of spikes will be highly beneficial for the image processing community as it describes a completely different, dynamic and energy-efficient manner the visual stimulus can be compressed. In this work, we show that the performance of the neuro-inspired quantizer is highly improved when the input signal is first transformed by DCT or DWT. To be able to measure the performance of the proposed architectures we used the Shannon Entropy to compute the number of bits required to store the compressed images and the Peak Signal to Noise Ratio (PSNR) to calculate the image distortion. Using these metrics, we show that the best rate-distortion trade-off is given by the architecture that consists of the DCT and the neuro-inspired quantizer.**

Keywords — neuro-inspired quantization, DCT, DWT, spikes, Leaky Integrate-and-Fire.

I. Introduction

We definitely live in the Big Data era, where the amount of data that are produced and shared every second is tremendously large to be able to be processed, stored and analyzed based on traditional algorithms. Compression is one of the most important Big Data challenges that the scientific community is urged to address to be able to efficiently transmit and/or store this enormous amount of information. The main disadvantages of the state-of-the-art compression algorithm are the complexity that is highly increasing over the years, the energy demands as a consequence of the high complexity, while at the same time the progress of this kind of algorithms is considered to be very slow if one considers that on average the scientific community needs a decade for the design, development and release of a new image/video compression standard [1][2]. Therefore, there is a clear and imminent need for establishing new architectures that will address the complexity of the current systems and propose an alternative way to deal with visual information in real time and in an energy-efficient manner. In this work, we propose that the visual system is able to transform the visual information into a very compact yet informative code of *spikes* in an alternative and energy-efficient manner that could be highly beneficial to image compression. Thus, we propose and compare the performance of some hybrid image compression architectures that first transform the input images using conventional and well-known transformations like DCT and DWT and then, they utilize a neuro-inspired quantization mechanism to reduce the spatial redundancy.

II. Proposed Architecture

As it was mentioned in Section I the proposed architecture first uses a DCT or a DWT transform. Due to the lack of space, we won't provide any information regarding these filters but we will focus on the neuro-inspired quantization and its special properties. The visual system is part of the central nervous system, so the proposed neuro-inspired quantizer was based on the study and modeling of the neural activity. The neuro-inspired quantizer is based on the Leaky Integrate-and-Fire (LIF) model [4] that approximates the neural structure and function by using a resistor-capacity electrical circuit by a current I according to the following equation:

$$I(t) = \frac{u(t)}{R} + C\frac{du}{dt}(t), \qquad (1)$$

This work has been co-financed by (I) the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH—CREATE—INNOVATE (project code: T2EDK- 03595, AdVISEr) and (ii) the HFRI and the GSRT under the grant agreement No. 330 (BrainSIM).

where R the resistance and C the capacitor. A neuron emits a spike if the input intensity I is stronger than a threshold θ, otherwise the neuron remains silent. Doutsi et. al. proposed in [4] that under the assumption that the input signal I is constant for a given time T it is possible to precisely calculate the time each neuron is excited, namely the spike arrival delay d, as follows:

$$d = \begin{cases} \infty & , \text{ if } \ RI < \theta \\ h = -CR \ln\left[1 - \dfrac{\theta}{RI}\right] & , \text{ if } \ RI > \theta \end{cases} \tag{2}$$

In addition, it was also proposed in [4] that being able to calculate the arrive delay it is possible to count the number of spikes each neuron emits within the observation window T:

$$N = \begin{cases} 0 & \text{if } \ RI < \theta \\ \left\lfloor \dfrac{T}{d} \right\rfloor & \text{if } \ RI > \theta \end{cases} \tag{3}$$

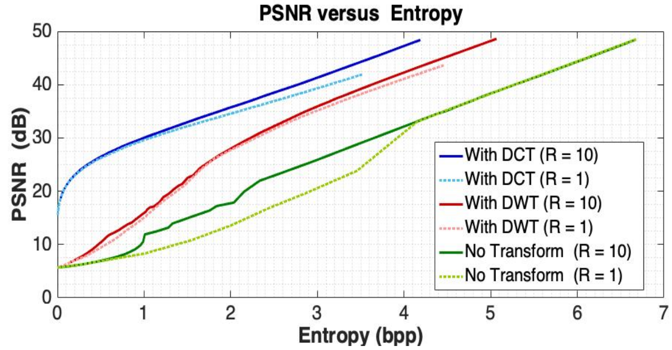
By counting the number of spikes, we succeed in reducing the spatial redundancy of the input signal while at the same time it is still possible to approximate the spike arrival delays $\tilde{d} = \frac{T}{N}$ and the input intensity of the current as follows:

$$\tilde{I} = \begin{cases} 0 & , \text{ if } \ RI < \theta \\ \dfrac{\theta}{R(1 - e^{-\frac{d}{RC}})} & , \text{ if } \ RI > \theta \end{cases} \tag{5}$$

As a result, this model receives as an input an image to be compressed and treats the value of the light intensity (luminance) of each pixel as a current that tries to stimulate a neuron. It has been proven in [4] that this model is an adaptive quantizer that according to the parameters tunning it might be uniform or non-uniform.

III. Experimental Results

In this section we present the experimental results of the proposed hybrid architectures that consist of a conventional transform (DCT or DWT) followed by the neuro-inspired quantizer. We compare the performance of this systems with the performance of the neuro-inspired quantizer when it is applied to the original image without any transform. The results confirm that the neuro-inspired quantizer actually helps to reduce the entropy of the original image as well as that the combination with the DCT or DWT transformation brings better results (see Fig. 1). More specifically, the contribution of the cosine transform is much more efficient than that of the wavelet transform. Fig. 2 offers a visual comparison of the reconstruction results of lena for two different entropies.



(a) DCT
H = 1.056 bpp
PSNR = 30.38 dB

(b) DCT
H = 4,187 bpp
PSNR = 48.39 dB

(c) DWT
H = 1.016 bpp
PSNR = 16.09 dB

(d) DWT
H = 4.272 bpp
PSNR = 43.92 dB`

(e) No Transform
H = 1.009 bpp
PSNR = 11.91 dB

(f) No Transform
H = 4.123 bpp
PSNR = 32.91 dB

IV. Conclusion

It is observed that the neuro-inspired method benefits from the "transition" of the image in the space of frequencies, namely from the use of transformation, as DCT or DWT organize the information of the image so that it can be compressed more effectively. A future goal is to compare this neuro-system with current compression systems as well as attempt to use it in dynamic data such as videos.

REFERENCES

[1] I. E. Richardson: The H.264 Advanced Video Compression Standard (Second Edition), A John Wiley and Sons, Ltd., Publication, 2010.

[2] Sullivan, G. J. et al., "Overview of the HEVC Standard." IEEE Trans. on Circuits and Systems for Video Technology, 22.12 (2012).

[3] W. Gerstner et. al, Spiking neuron models: Single Neurons, Populations, Plasticity, Cambridge University Press, 2002.

[4] E. Doutsi, L. Fillatre, M. Antonini and P. Tsakalides, "Dynamic Image Quantization Using Leaky Integrate-and-Fire Neurons," in IEEE Transactions on Image Processing, vol. 30, pp. 4305-4315, 2021.