Proposal for Unsupervised Image Compression via Cycle Consistency

ECE 285 Final Project, Spring 2020

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1. Motivation

Deep learning has been useful these years in so many research sub-fields of image processing while image compression is a typical one. Traditional image compression methods are mostly based on transform-coding such as BPG (G. J. Sullivan & Wiegand, Dec 2012) and JPEG (Taubman & Marcellin, 2013). With the recent advances in deep learning, neural networks have been applied to image compression with promising results.

2. Introduction

We think the problem of image compression of quality loss is a **dual task of image super-resolution**. Inspired by CycleGAN (Jun-Yan Zhu & Efros, 2017), we propose a direct and simple deep learning based image compression algorithm via **cycle consistency** (Figure 1) where the "symmetrical" decoder reconstructs the compressed image into source image if we find a encoder which can be a deep neural network for compression. The encoder-decoder is successful whenever the fully trained decoder reconstructs the compressed code into source image. Our proposed algorithm is also inspired by (Caglar Aytekin & Hannuksela, 24 May 2019) with some additional design and details in **Methodology**.

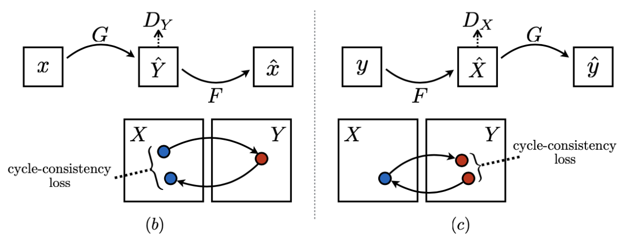

Figure 1. Conception of Cycle Consistency

3. Role of Team

3.1. Member 1: Methodology

As mentioned above, we want to train a encoder-decoder with input a single image I and compressed $\sigma(I)$. To construct the training process, We plan to design a prepositive down-sampling block with multiple residual blocks as encoder and its dual or called symmetrical structure, rear up-sampling block with multiple residual blocks as decoder. The encoder and decoder should share parameters of each layer correspondingly. The form or the size of compressed code could be modified by changing the last layer of encoder. In addition, the compressed code should be as simple or say "sparse" as possible. We also plan to design two loss functions with cyclic consistency loss and compression loss, and combine them together as total training loss.

3.2. Member 2: Dataset and Evaluation

We plan to evaluate our algorithm on open image datasets with high resolution images and compare with different versions of the images. The evaluation matrix we focus on are **Compression Rate, Processing Speed per hundred images and Reconstruction Quality**.

References

Caglar Aytekin, Francesco Cricri, Antti Hallapuro Jani Lainema Emre Aksu and Hannuksela, Miska. A compression objective and a cycle loss for neural image compression. *arXiv:1905.10371v1 [eess.IV]*, 24 May 2019.

G. J. Sullivan, J. R. Ohm, W. J. Han and Wiegand, T. Overview of the high efficiency video coding (hevc) standard. *IEEE Transactions on Circuits and Systems for Video Technology, 22(12)*, pp. 1649–1668, Dec 2012.

Jun-Yan Zhu, Taesung Park, Phillip Isola and Efros, Alexei A. Unpaired image-to-image translation using cycle-consistent adversarial networks. *arXiv preprint arXiv:1703.10593*, 2017.

Taubman, D. and Marcellin, M. Jpeg2000 image compression fundamentals, standards and practice. *Springer Publishing Company, Incorporated*, 2013.