Application of Convolutional Neural Network in single image encoding

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Abstract

Efficient image compression algorithms influence the field of communications significantly, as image transmission accounts for a substantial portion of data usage. Conventional algorithms, such as JPEG and PNG, work reliably and consistently, but does not take advantage of various features of the target image.

Recent advances in the field of Convolutional Neural Networks (CNN) has showed that CNN models work well on various image processing tasks, such as feature extracting and super-resolution. We suggest a novel image compressing architecture, Compressing CNN (CCNN), which applies feature extraction and super-resolution imaging via CNN models to the task of image compression.

Our experiments concluded that CCNN outperforms conventional image compression algorithms in certain ranges of compression ratios.

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Introduction & Goal

Introduction

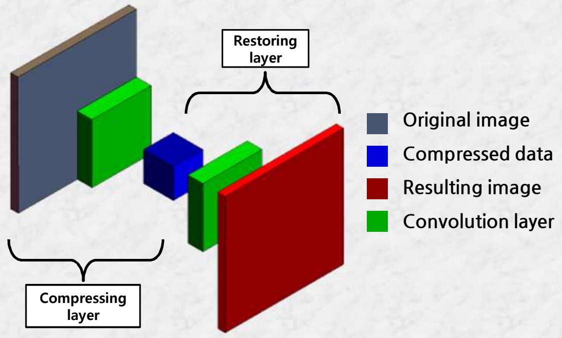
JPEG, the conventional image compressing algorithm, has a high compression rate, but data loss occurs while compressing. This research suggests a novel algorithm, **Compressing Convolutional Neural Network (CCNN)**, which implements feature extraction and super-resolution imaging techniques via CNN.

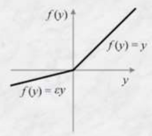
Goal

Implementing CCNN, a Neural Network model for image compression.

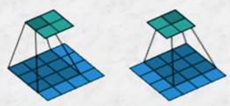
Comparing CCNN and JPEG regarding compression rate and precision across various settings.

Structure





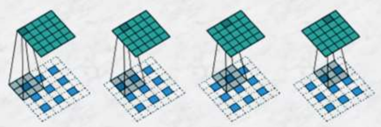
Leaky ReLU function



Convolution

Compressing layer

When an image of dimension (H, W, D) goes through a compression layer with a compression ratio of λ, its size become $[H/\lambda], [W/\lambda], D\lambda$, shrinking data λ times. We implement this by setting the stride of the convolutional layer to λ and using zero-padding. The size of the filter ranged from 10 ~ 50; Leaky ReLU was used as an activation function; its slope ε ranged from 0.0~0.15.



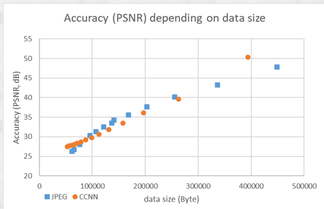
Transposed Convolution

Restoring layer

The restoring layer transforms compressed data back into the same dimension with the original image by using transposed convolution. The stride and the slope of Leaky ReLU was the same as compressing layer, and the size of the filter ranged from 10 ~ 50. The saturate_cast function in the Tensorflow library was used to convert processed data from floating point to unsigned integer, without any potential overflow or underflow risks.

Results

From the left, segment of original, CCNN and JPEG.

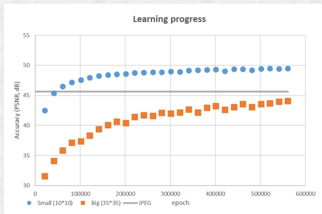


Comparison of **Accuracy (PSNR)** depending on **data size**.

Original image size: 788KB

JPEG

CCNN



Comparison of **Accuracy (PSNR)** depending on **filter size**.

JPEG data is gained from interpolation.

Small filter (10*10)

Big filter (35*35)

JPEG

Image compressed by ratio of 3

Original image : **604KB**

Compressed data : **199KB**

Conclusion

Different compression artifacts

CCNN makes 'smudges', JPEG makes square 'blocks'.

Outperforms JPEG in certain ranges of compression rates.

CCNN performs better in extreme cases (ratio larger than 10, or smaller than 2.5).

Smaller convolution filters are better overall.

Size doesn't affect the quality, but **models with smaller filters learn faster** than the ones with larger filters.

Discussion

Compromises

- **Preprocessing** is required. To achieve acceptable performance, at least 10 minutes of training is needed.
- A **Restoring layer** is required. In this research, the entire model is about 50 KB.

Follow-up

- Video compression with CCNN
- Hyperparameter searching
- Using multi-layer convolution or transposed convolution

Reference

[1] Krizhevsky, A. et al. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems 25 1097-1105 (2012)

[2] Dong, C. et. al. Learning a Deep Convolutional Network for Image Super-Resolution, in Proceedings of European Conference on Computer Vision (ECCV) (2014)

[3] Boudjelal, A. et. al. A Novel Kernel-Based Regularization Technique for PET Image Reconstruction, http://www.mdpi.com/2227-7080/5/2/37 Technologies 5(2) 37 (2017)

[4] Dumoulin, V. et. al. A guide to convolution arithmetic for deep learning, https://arxiv.org/abs/1603.07285 (2016)

[5] Franzen, R. Kodak Lossless True Color Image Suite. http://r0k.us/graphics/kodak/ (1999)