

A comparative analysis of the state-of-the-art lossless image compression techniques

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Abstract. Lossless data reduction is essential for data transmission over the Internet and the storage of data in a digital device when data loss is not permitted. The application of image compression is essential for image storing, image classification, and image recognition, and image compression techniques compress an image by reducing redundancy in the image. Many image compression standards have already been developed. This article compares the most popular state-of-the-art lossless image compression techniques, and the methods are evaluated based on the bits per pixel or compression ratio. Finally, we recommend which of the algorithms is better for a few different datasets.

1 Introduction

According to Cisco's Annual Internet Report [1], digital media is responsible for about 80% of the world's Internet traffic, and it is growing. The 6th edition of the Data Never Sleeps report [27] shows that every person on Earth will create 1.7 MB of data per second by 2020, and the number of internet users is increasing significantly. Typically, storing an original image on a digital device requires a lot of storage and takes a long time to transfer over the Internet. An image compression technique reduces the number of bits in an image and enables image transmission at low bandwidth connections at high speeds [2-3]. Image compression techniques are divided into lossless and lossy methods [13-14]. A lossless method perfectly reproduces the original image from the encoded form [41,46], and lossy compression allows a slight loss [4-8].

There are two types of lossless image compression methods: learning and non-learning techniques. Portable network graphics (PNG), JPEG 2000, WebP, and the Free Lossless Image Format (FLIF) are the most popular techniques in the non-learning category. On the other hand, there are many learning-based techniques, such as L3C, IDF, SReC, etc. [9-10].

This article contains a comparison of the performance of the most popular non-learning and learning lossless image compression methods. The rest of this article is organized as follows: Section 2 briefly explains the state-of-the-art lossless image

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compression techniques. Section 3 presents the experimental results and analysis, and the paper concludes in section 4.

2 Background studies

JPEG-LS [28-29], an improved version of lossless JPEG that was developed based on LOCO-I (Low Complexity Lossless Compression for Images), provides more compression than lossless JPEG because JPEG-LS can perform a good decorrelation. The context-based, adaptive, lossless image codec (CALIC) [30], a gradient-adjusted predictor-based compression technique, gives more compression than JPEG-LS. PNG [15-17], a patent-free replacement for the GIF, is a lossless image compression method: it compresses an image using a prediction [18] and an entropy coding technique [19]. JPEG 2000, a wavelet-based compression method, provides more compression than PNG. However, it takes more time to encode and decode an image [20-21]. WebP was developed in 2010 based on VP8 [22] and provides more compression than PNG and JPEG 2000. One form of context-adaptive binary arithmetic coding (CABAC) is Meta-Adaptive Near-zero Integer Arithmetic Coding (MANIAC), which was used to develop FLIF [23-24]. FLIF provides better compression for any kind of image than the state-of-the-art non-learning lossless image compression standard [25]. However, it is too slow, and currently, no browser supports it [26].

Schiopu et al. [31] proposed a lossless image compression strategy called MP-CNN, which was developed based on a macro-pixel prediction technique and convolutional neural networks (CNNs). The MP-CNN model has 57 layers, including the following layer types: 3D convolution, 2D convolution, batch normalization, ReLU activation, and reshape. The model also consists of two group layers: GoL-3D [N] and GoL-2D [N]. GoL-3D performs 3D convolution with N filters of size 3x3x3, batch normalization, and a ReLU operation in the first, second, and third layers, respectively. GoL-2D, on the other hand, performs 2D convolution with N filters of size 3x3 in the first layer. The second and third layers perform batch normalization and ReLU activation operations, respectively. Later, the authors also proposed another lossless image compression method called CBPNN using deep learning [33]. CBPNN is a combination of the context-based bit plane codec (CBP) and the IResLNN predictor [32]. CBPNN performs 13.7% better than MP-CNN. L3C [10] is a fully parallel hierarchical probabilistic lossless image compression technique with auxiliary feature representations, and it outperforms PNG, JPEG 2000, and WebP. It also provides a better performance than PixelCNN [34], PixelCNN++ [35], and MS-PixelCNN [36].

3 Experimental results and analysis

In this section, the state-of-the-art methods are compared based on their performance on a few different datasets. The methods are evaluated based on the compression ratio (CR) or the bits per pixel (BPP), where the BPP is just the opposite of the CR. The BPP is the ratio of the uncompressed image size, ($Size_{uncompressed}$), to the compressed image size, ($Size_{compressed}$), which is calculated using equation 1. Here, N_{Pix} represents the number of pixels in an image.

$$BPP = \frac{Size_{compressed}}{N_{Pix}} \quad 1$$

Ionut et al. [33] present the experimental results on the EPFL [37] and UVG-TUT [38] datasets, which are shown here in Table 1 and Table 2, respectively. Table

Table 1: Comparison of BPP for the EPFL dataset [37]

	JPEG-LS [28]	CALIC [45]	FLIF [23]	MP-CNN [31]	CBPNN
Training	3.847	3.730	3.127	3.098	2.733
Test	3.786	3.671	3.085	3.180	2.797
Total	3.791	3.676	3.089	3.173	2.792

Table 2: Comparison of BPP for the UVG-TUT dataset [38]

Video Sequence (600 Frames)	Non-learning methods				CBPNN	
Name	HEVCIntra [44]	JPEG-LS [28]	FLIF [23]	CALIC [45]	FAST profile	SLOW profile
Beauty	3.758	3.584	3.452	3.423	3.405	3.397
Bosphorus	3.119	2.511	2.475	2.428	2.387	2.379
HoneyBee	3.566	3.108	3.009	2.971	2.960	2.944
Jockey	3.175	2.848	2.759	2.750	2.715	2.705
ReadySteadyGo	3.469	2.810	2.751	2.681	2.625	2.615
ShakeNDry	4.156	3.354	3.229	3.147	3.159	3.148
YachtRide	3.411	2.692	2.654	2.562	2.516	2.506
Average (BPP)	3.522	2.987	2.904	2.852	2.824	2.813

Table 3: Comparison of BPP for the ImageNet64 [39] and OpenImage [40] datasets

Method Name	ImageNet64 [35]	OpenImage [36]
PNG [43]	17.22	12.09
WebP [43]	13.92	9.09
FLIF [43]	13.62	8.61
IDF [42]	11.70	8.28
L3C [10]	13.26	8.97
SReC [43]	12.90	8.10
MPSMCT	11.33	7.48

1 shows that CBPNN outperforms the JPEG-LS, CALIC, FLIF, and MP-CNN by 35.4%, 31.3%, 10.6%, and 13.7%, respectively. Table 2 shows that on average, CBPNN outperforms other methods. However, on average, the SLOW profile of CBPNN provides 0.391% better results than the FAST profile of CBPNN.

Pixel-wise autoregressive statistical models based on image compression methods provide good performance. However, we can use them in real applications for sequential processing. Zhang et al. proposed a multi-scale progressive statistical model-based lossless image compression technique (MPSMCT), using the advantages of the multi-scale strategy and the pixel-wise procedure. The authors examine two image datasets: ImageNet64 [39] and OpenImage [40], and the experimental results are shown in Table 3. Table 3 shows that MPSMCT provides 51.986%, 22.86%, 20.212%, 3.266%, 17.034%, and 13.857% better results than PNG, WebP, FLIF, IDF, L3C, and SReC, respectively.

4 Conclusion

In this study, we compared the state-of-the-art learning and non-learning lossless image compression methods based on four datasets: EPFL Light-field, UVG-TUT,

ImageNet64, and OpenImage. An analysis based on the experiment results shows that CBPNN outperforms the HEVCIntra, JPEG-LS, FLIF, and CALIC methods for the EPFL Light-field and UVG-TUT datasets. On the other hand, MPSMCT surpasses PNG, WebP, FLIF, IDF, L3C, and SReC for the ImageNet64 and OpenImage datasets. In future work, we plan to develop a hybrid learning-based lossless image compression technique using a multi-scale progressive statistical model.

References

- 1 Perspectives, E. and Report, C., 2021. Cisco Annual Internet Report - *Cisco Annual Internet Report* (2018–2023) White Paper. Cisco.
- 2 Rahman, M. and Hamada, M., 2020. Burrows–Wheeler Transform Based Lossless Text Compression Using Keys and Huffman Coding. *Symmetry*, 12(10), p.1654.
- 3 Rahman, M.A. and Hamada, M., 2019, October. A semi-lossless image compression procedure using a lossless mode of JPEG. In *2019 IEEE 13th International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoc)* (pp. 143-148). IEEE.
- 4 Sayood, K., 2017. Introduction to data compression. *Morgan Kaufmann*.
- 5 Kotha, H.D., Tummanapally, M. and Upadhyay, V.K., 2019, May. Review on Lossless Compression Techniques. In *Journal of Physics: Conference Series* (Vol. 1228, No. 1, p. 012007). IOP Publishing.
- 6 Rahman, M., Hamada, M. and Shin, J., 2021. The Impact of State-of-the-Art Techniques for Lossless Still Image Compression. *Electronics*, 10(3), p.360.
- 7 Storer, J.A., 1987. Data compression: methods and theory. *Computer Science Press, Inc.*.
- 8 Salomon, D. and Motta, G., 2010. Handbook of data compression. *London; New York: Springer*.
- 9 Schiopu, I. and Munteanu, A., 2019. Deep-learning-based lossless image coding. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(7), pp.1829-1842.
- 10 Mentzer, F., Agustsson, E., Tschannen, M., Timofte, R. and Gool, L.V., 2019. Practical full resolution learned lossless image compression. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 10629-10638).
- 11 Mentzer, F., Gool, L.V. and Tschannen, M., 2020. Learning better lossless compression using lossy compression. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 6638-6647).
- 12 Zhang, Y., 2015, July. The studies and implementation for conversion of image file format. In *2015 10th International Conference on Computer Science & Education (ICCSE)* (pp. 190-193). IEEE.
- 13 Rahman, M.A., Islam, S.M.S., Shin, J. and Islam, M.R., 2018, December. Histogram alternation based digital image compression using Base-2 coding. In *2018 Digital Image Computing: Techniques and Applications (DICTA)* (pp. 1-8). IEEE.

- 14 Rahman, M.A., Rabbi, M.F., Rahman, M.M., Islam, M.M. and Islam, M.R., 2018, September. Histogram modification based lossy image compression scheme using Huffman coding. In *2018 4th International Conference on Electrical Engineering and Information Communication Technology (iCEEiCT)* (pp. 279-284). IEEE.
- 15 Libpng.org. 2020. PNG specification: Filter Algorithms. [online] Available at: <http://www.libpng.org/pub/png/spec/1.2/PNG-Filters.html>.
- 16 Roelofs, G. and Koman, R. 1999. PNG: The definitive guide. *O'Reilly & Associates, Inc.*.
- 17 Wilbur, C. 2001. PNG: The definitive guide. *Journal of Computing in Higher Education*, 12(2), pp.94-97.
- 18 Paeth, A.W. 1991. Image file compression made easy. In *Graphics Gems II* (pp. 93-100). *Morgan Kaufmann*.
- 19 Rahman, M. and Hamada, M., 2019. Lossless image compression techniques: A state-of-the-art survey. *Symmetry*, 11(10), p.1274.
- 20 Zhang, J. and Le, T.M. 2010. A new no-reference quality metric for JPEG 2000 images. *IEEE Transactions on Consumer Electronics*, 56(2), pp.743-750.
- 21 Liu, Z., Karam, L.J. and Watson, A.B. 2006. JPEG 2000 encoding with perceptual distortion control. *IEEE Transactions on Image Processing*, 15(7), pp.1763-1778.
- 22 Si, Z. and Shen, K., 2016. Research on the WebP image format. In *Advanced Graphic Communications, Packaging Technology and Materials* (pp. 271-277). *Springer, Singapore*.
- 23 Sneyers, J. and Wuille, P., 2016, September. FLIF: Free lossless image format based on MANIAC compression. In *2016 IEEE International Conference on Image Processing (ICIP)* (pp. 66-70). *IEEE*.
- 24 Soferman, N., 2021. FLIF, The New Lossless Image Format That Outperforms PNG, Webp And BPG. [online] Cloudinary. Available at: https://cloudinary.com/blog/flif_the_new_lossless_image_format_that_outperforms_png_webp_and_bpg
- 25 Flif.info. 2021. FLIF - Free Lossless Image Format. [online] Available at: <https://flif.info/>.
- 26 Flif.info. 2021. FLIF - Example. [online] Available at: <https://flif.info/example.html>
- 27 Domo.com. 2021. How much data is generated every minute?. [online] Available at: https://www.domo.com/assets/downloads/18_domo_data-never-sleeps-6+verticals.pdf [Accessed 29 September 2021].
- 28 Weinberger, M.J., Seroussi, G. and Sapiro, G. 2000. The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS. *IEEE Transactions on Image Processing*, 9(8), pp.1309-1324.
- 29 Weinberger, M.J., Seroussi, G. and Sapiro, G. 1996, March. LOCO-I: A low complexity, context-based, lossless image compression algorithm. In *Proceedings of Data Compression Conference-DCC'96* (pp. 140-149). *IEEE*.
- 30 Wu, X., 1996, March. An algorithmic study on lossless image compression. In *Proceedings of Data Compression Conference-DCC'96* (pp. 150-159). *IEEE*.

- 31 Schiopu, I. and Munteanu, A., 2018, October. Macro-pixel prediction based on convolutional neural networks for lossless compression of light field images. *In 2018 25th IEEE International Conference on Image Processing (ICIP)* (pp. 445-449). IEEE.
- 32 Schiopu, I. and Munteanu, A., 2018. Residual-error prediction based on deep learning for lossless image compression. *Electronics Letters*, 54(17), pp.1032-1034.
- 33 Schiopu, I. and Munteanu, A., 2019. Deep-learning-based lossless image coding. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(7), pp.1829-1842.
- 34 Van Oord, A., Kalchbrenner, N. and Kavukcuoglu, K., 2016, June. Pixel recurrent neural networks. *In International Conference on Machine Learning* (pp. 1747-1756). PMLR.
- 35 Salimans, T., Karpathy, A., Chen, X. and Kingma, D.P., PixelCNN++: A PixelCNN Implementation with Discretized Logistic Mixture. *ICLR*.
- 36 Reed, S., Oord, A., Kalchbrenner, N., Colmenarejo, S.G., Wang, Z., Chen, Y., Belov, D. and Freitas, N., 2017, July. Parallel multiscale autoregressive density estimation. *In International Conference on Machine Learning* (pp. 2912-2921). PMLR.
- 37 Plenodb.jpeg.org. 2021. JPEG Pleno Database: EPFL Light-field data set. [online] Available at: <http://plenodb.jpeg.org/lf/epfl>.
- 38 Ultra Video Group. Tampere University of Technology. *Test Sequences*. Available: <http://ultravideo.cs.tut.fi/#testsequences>
- 39 Chrabaszcz, Patryk and Loshchilov, Ilya and Hutter, Frank. A downsampled variant of imagenet as an alternative to the cifar datasets.arXiv preprint arXiv:1707.08819, 2017.
- 40 Krasin, I., Duerig, T., Alldrin, N., Ferrari, V., Abu-El-Haija, S., Kuznetsova, A., Rom, H., Uijlings, J., Popov, S., Veit, A. and Belongie, S., 2017. Openimages: A public dataset for large-scale multi-label and multi-class image classification. Dataset available from <https://github.com/openimages>, 2(3), p.18.
- 41 Rahman, M.A. and Hamada, M., 2021. Lossless text compression using GPT-2 language model and Huffman coding. *In SHS Web of Conferences* (Vol. 102, p. 04013). EDP Sciences.
- 42 Hoogeboom, E., Peters, J.W., Berg, R.V.D. and Welling, M., 2019. Integer discrete flows and lossless compression. *arXiv preprint arXiv:1905.07376*.
- 43 Cao, S., Wu, C.Y. and Krähenbühl, P., 2020. Lossless image compression through super-resolution. *arXiv preprint arXiv:2004.02872*.
- 44 Sullivan, G.J., Ohm, J.R., Han, W.J. and Wiegand, T., 2012. Overview of the high efficiency video coding (HEVC) standard. *IEEE Transactions on circuits and systems for video technology*, 22(12), pp.1649-1668.
- 45 Wu, X. and Memon, N., 1997. Context-based, adaptive, lossless image coding. *IEEE transactions on Communications*, 45(4), pp.437-444.
- 46 Rahman, Md Atiqur and Hamada, Mohamed, 2021. PCBMS: A Model to Select an Optimal Lossless Image Compression Technique. *IEEE Access*, 9, pp.167426 - 167433.