Shrinking Big Data: A Novel Compression Algorithm for LIDAR Elevation Maps

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Background

Image courtesy of Velodyne LIDAR

Recent years have seen increasing use of LIDAR, a method of capturing the depth of surrounding terrain by latency in laser pulses, to facilitate automation technologies such as Automatic Ground Collision Avoidance for aircraft (Auto-GCAS), autonomous vehicles, and robotics. These use cases, which have become some of the most exciting work in academia, supplement the traditional usage of LIDAR as a technology facilitating precision agriculture, surveying, and land management. **Since its inception, the detection method has provided unparalleled accuracy and data abundance, which has been considered heavily in improvements to renewable energy, infrastructure development, and autonomy**. The density of LIDAR gives autonomous systems the information they need to make informed navigation and traffic decisions. As such, Google Waymo, Boston Dynamics, and Lockheed Martin have invested highly into LIDAR sensing to inform their autonomous systems between robotics, navigation, and aeronautics with mounted sensors mapping a three-dimensional environment for the vehicle as it travels through space.

Problem

LIDAR data density comes at a cost: **even very small areas mapped in LIDAR can have file sizes in the gigabyte to terabyte range, making the data impossible to transfer and expensive to store**. LIDAR has been limited in its accessibility due to the high cost of high-quality sensors and the unpredictable reliability of concurrently generated data. Pre-analyzed data is a proposed solution to this problem; yet, as improvements in digital telemetry begin to slow**, the task is now one of data encoding and digital compression to facilitate the vast data transfers required for autonomous, life-saving technology**.

Objective

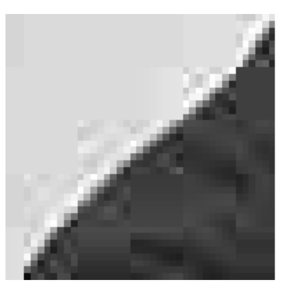
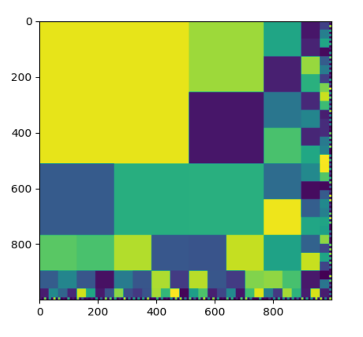


Image codecs largely rely on the tolerance of the human eye to mask imperfections within an image. JPEG, for example, uses the intersection of cosine waves to model data, a notion that leads to unbelievable compression, but fails at closer inspection. Examine a black-and-white edge that undergoes a high efficiency DCT transform (JPEG)

The codec obscured the edge and introduced uncertainty into the raster. For real-world geospatial scans, this errant data (artifacting) has destroyed the integrity of the raster and cannot be used for autonomous decision making. **A novel codec must be developed that can compete with high efficiency transforms, while programmatically ensuring no artifacts. This board presents a novel algorithm, General Purpose Geospatial Compression (GPGC), that fills this objective.**

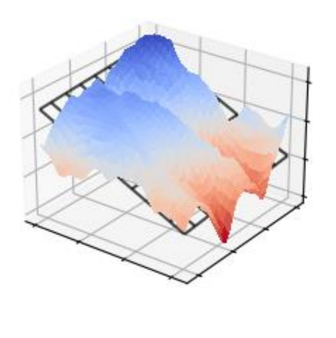
Encoding Procedures

Preprocessing



GPGC relies on data to be in a consistent 2^n square size to allow the most efficient encoding and *quadrisections* possible. Therefore, data is preprocessed into a *mosaic* of 2^n sized fragments that fill bands radiating from the top left origin of the raster. Each fragment in the mosaic is compressed individually and encoded as a separate tree structure and stitched together in the decoding step.

Linear Regression Analysis



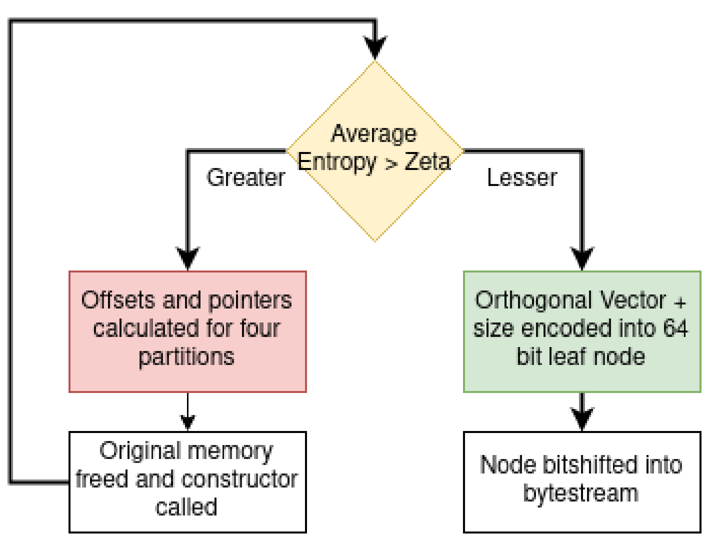
Within each fragment a block of data is passed by pointer to form a partition object. Within this, a regression plane is fitted with a LU decomposition operation performed on a $3 \times n$ matrix formed using the block, solving for an orthogonal vector that forms the plane. Here you can visually see a meshed geospatial datablock that has been fitted a least squares regression plane

The $\hat{\imath}, \hat{\jmath}, \hat{k}$ vector components of the LSRP are stored as 16-bit IEEE754 Half Precision Floats in 64-bit leaf node structure `gpgc_vector`. From the plane, each differential is evaluated and accumulated into an unsigned long which is distributed across each point in the block. However, instead of evaluating the pure differential (as GEDACS and ECW do), GPGC calculates a z-score for each point based on a supplied compression parameter sigma, representing the standard deviation of acceptable errors. From this, the integral of probability density function to z-score is calculated, and the information entropy of each point with a partition C with size M is calculated as a function of the probability at any point (m, n)

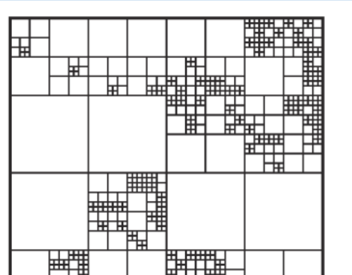
$$\mathrm{P}(\mathrm{C}_{mn}) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-x^2}{2}} dx \qquad \mathrm{H}(\mathrm{C}) = \sum_{n=1}^{M} \sum_{m=1}^{M} \frac{\log_2 P(C_{mn})}{M^2}.$$

Recursive Quad Tree Generation

Average information entropy per point evaluated with the above formulae and compared to compression parameter zeta. If entropy is greater than the threshold allowed, the offset and pointer for the block of memory are allocated and four new child partitions are constructed with size 2^{n-1} assuming the original had size 2^n. Hence lay the beauty of the above mosaicing system. This recursive pattern ensures that once the maximum depth is reached, the data will be organized in a depth-first search, an aspect of the encoding that is essential for the decoding process. If the entropy is found to be within the acceptable range zeta, the memory holding the structure gpgc_vector is cast to an integer and bitshifted into the bytestream, writing the resultant file in a dense binary of encoded partitions. The tree structure depicted below is an illustration of the hierarchical relationship of nodes that forms the basis for the codec. Similarly, the decision and recursion are visualized in a decision flow chart:


Average Entropy > Zeta
Greater
Lesser
Offsets and pointers calculated for four partitions
Orthogonal Vector + size encoded into 64 bit leaf node
Original memory freed and constructor called
Node bitshifted into bytestream

Decoding

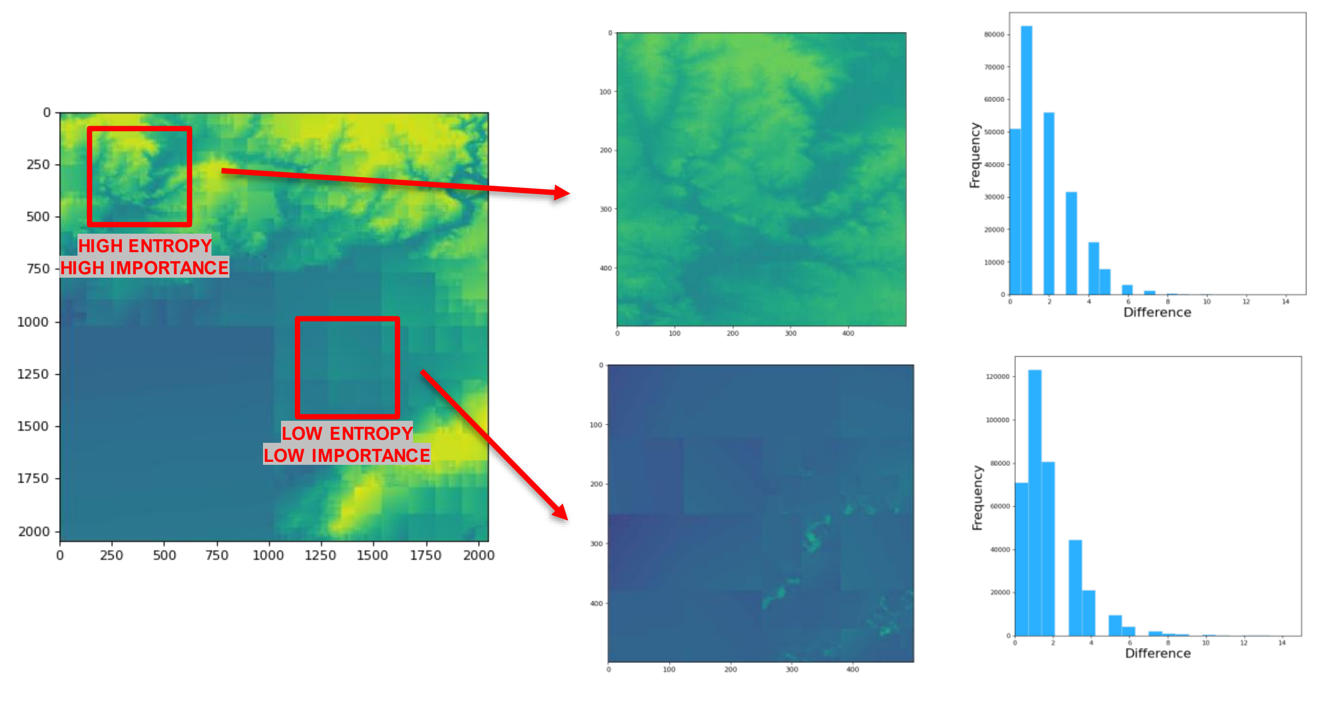


The GPGC decoder relies on a depth-first search of the above quadtree structure. It unpacks each element into two 16-bit floats, as well as a two 16-bit integers representing the $\hat{k}$ vector component and $\log_2 M$, respectively. The project takes a novel approach to a depth-first search of an unknown-size quadtree, relying on a stack-based model. When a new size is added, it is placed at the top of the stack and substacks are created within it that accumulate the size of leaf nodes until the square of their size is met. This algorithm can determine the offsets for each leaf node in a raster. The concept of this decoder is visualized in the figure above. From here, it is simple to create a raster with the orthogonal vectors. The orthogonal vectors are multiplied by the index within the partition following $z = ix + jy + k$ to calculate each point. The decoder runs in $O(n)$ linear time, superseding existing methods of quad-tree decoding such as that of GEDACS and some JPEG2000 implementations.

Entropy Encoding

The GPGC algorithm is different from other encoding schemes as it considers information entropy, which measures the uncertainty or unpredictability of a dataset. This mathematical concept has been widely used in telecommunications and signal processing for filtering meaningful data from noise. Information entropy is calculated as the minimum number of bits required to represent a dataset. It helps the algorithm to process data in a human-like, intelligent manner. If a dataset has low entropy, meaning it is predictable and unchanging, its data points can be compressed more aggressively. On the other hand, high entropy datasets require more accuracy and high-resolution information to be processed effectively.

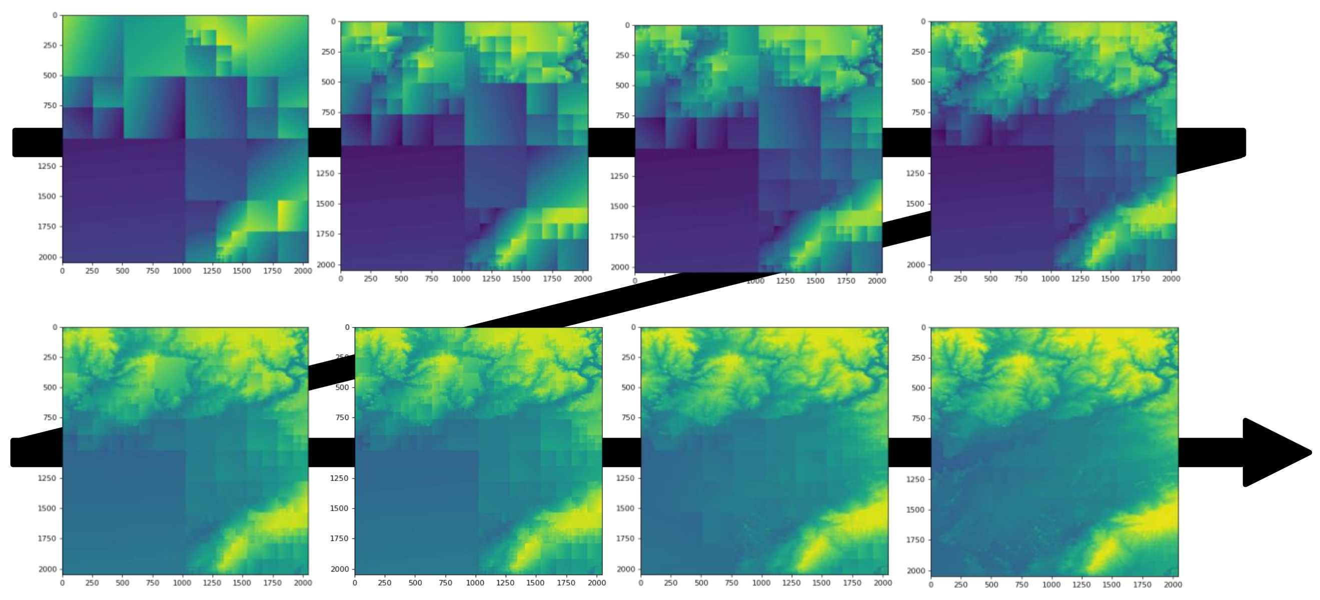
The partitioning entropy evaluation of GPGC sets the resolution of the decoded data by using variable-size partitions within the decoded hierarchical tree structure. In high-entropy areas, it achieves nearly pixel-perfect accuracy, while in low-entropy areas, it skips over smaller, less important features. The sensitivity of the algorithm can be adjusted depending on the application, with two runtime flags available. This algorithm is different from JPEG, which partitions all data into 8 x 8 chunks and calculates the Discrete Cosine Transform for encoding. However, geospatial data has predictable patterns and can be entropy coded more efficiently, which the GPGC algorithm takes advantage of. The algorithm would be even more efficient if the DCT was generated for all partitions, but it is not suitable for real-world LIDAR data.



We can inspect both visually and quantitatively the quality of this compression. For the high entropy region, the data is visually lossless. While we *can* inspect the partition borders in the low entropy region, where the compression has been more aggressive, the differences between each border is quite small and inessential for autonomous systems. Still, GPGC has done an outstanding job preserving the small terrain features that appear in a slight green.

Compression Snapshots

GPGC's set partition code is a refining algorithm. It makes no assumptions about the number of partitions that it will take to compress a raster to the desired entropy threshold: a key difference from related partitioning algorithms such as JPEG2000. A simple way to understand what exactly is happening experimentally is to visualize the compression while it is happening. The following images are in order, showing the process of partitioning the raster from large square blocks to visually lossless data.



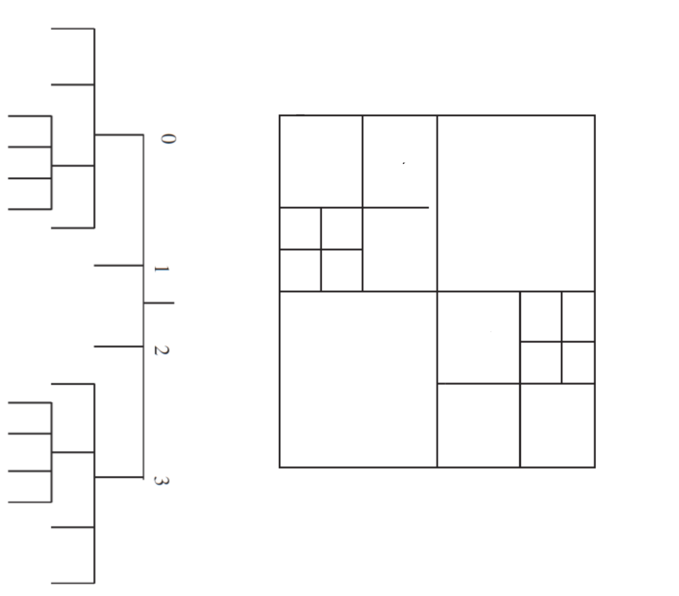
Consider that the encoding process does not happen linearly, we can see how it immediately focuses its efforts to compressing the high information mountains, while letting the accuracy of the plains below fall behind.

Encoding Schema

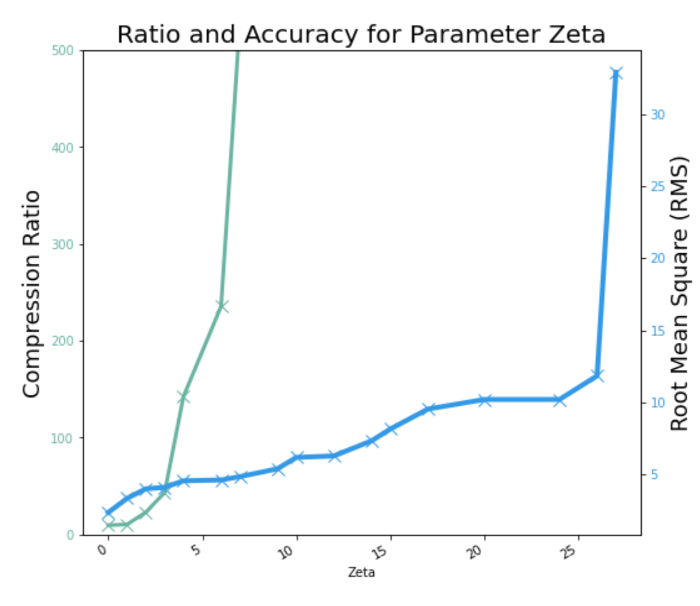
0001110010101010 1010001011101110 0101110010101010 0001000101110111 0

$\hat{\imath}$ *vector component (16-bit float)*	$\hat{\jmath}$ *vector component (16-bit float)*	$\hat{k}$ *vector component (16-bit int)*	$\log_2 M$ *(16-bit int)*

```
 0.607422   0.0917969 210 16
-0.107117   1.51172   216 16
-0.550293   1.33594   216 8
-0.053558   1.44629   211 8
-0.367432   1.84668   228 8
-0.767578   2.10938   224 8
 0.740723   0.672363  234 8
-0.550293   1.33594   219 16
 0.34668    0.679688  243 32
 0.916504  -0.532715  230 32
 2.17188   -0.710938  238 16
-0.604492   0.0419006 244 8
 0.380371   0.718262  224 8
 0.194214   0.801758  224 8
 0.284424   0.812988  241 8
-0.380127   0.404785  250 16
 0.081665   0.337891  240 16
```

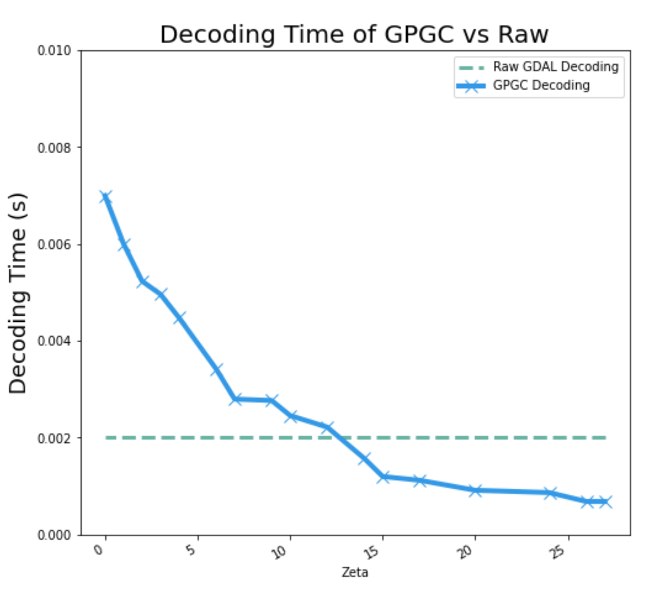


Performance



The above line graph plots the Root Mean Square Error (RMS) against the Compression Ratio for GPGC. Note the differing axes for each quantity. The algorithm is designed to work anywhere with a zeta between 1 and 25. However, the best results are achieved between 2-5. At a zeta of 1, the compression ratio is often less than 2, while greater than 5, the error because unsuitable for real data and obvious on visual inspection.

For all measurements, a very high information entropy threshold was used so as show the relationship without interference.



An often overlooked but highly important part of a compression algorithm is its decoding speed. GPGC has a novel decoding scheme for searching a quad tree structure. The industry tool for decoding GeoTIFF and DTED rasters is GDAL. GPGC is compared against the GDAL uncompressed speed at various values of zeta. Interestingly, above a zeta of 15 it becomes faster than GDAL. The only explanation for this is that the bare-bones implementation of GPGC skips the complex header generics of the TIFF specification, allowing for slightly faster encoding when few operations need to be performed

Testing

GPGC is compared against a total of seven algorithms. Three geospatial algorithms are identified: GEDACS (NASA), MrSID (Los Alamos National Laboratory), and ECW (Hexagon AB). Three binary codecs are identified: ZSTD (Facebook), PACKBITS (Apple), and Deflate (aka. Lempel-Ziv 77) (MIT). Finally, GPGC is compared against the JPEG lossy image algorithm, seen as the golden standard for extremely high-efficiency compression, although the reasons for its unsuitable use have been explored thoroughly in this board.

Using the GDAL CLI and the proprietary MSVC solution for GEDACS, each possible codec was implemented onto 135 randomly selected United States Geographical Survey Continental 1-arc second rasters (12,967,201 points per raster) captured from the SRTM project. This dataset was chosen due to its unprecedented reliability, and the simplicity of the existing encoding, ensuring as many of the codecs could be tested as possible. Testing was done inside of a Jupyter IPython notebook where each file was evaluated for compression ratio and mean average error.

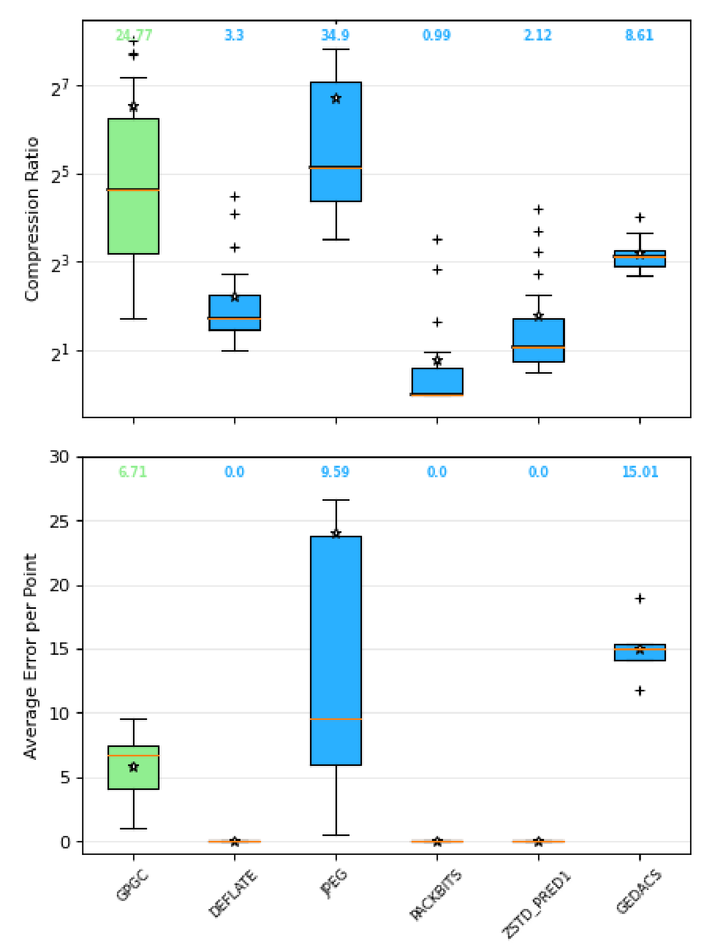
Results

Compression Benchmarks

Compression Algorithm	Comp. Ratio 25%	Comp. Ratio Med.	Comp. Ratio 75%	Percent Decrease	Average Error
GPGC	**8.2**	**24.7**	**72.8**	**95.97%**	**6.71**
GEDACS	7.7	8.48	9.2	88.21%	15.7
MrSID	4*	n/d*	10*	n/d*	0
ECW	n/d*	10*	15*	90%*	n/d
ZSTD PRED1	1.7	2.12	4	52.12%	0

* = Closed-source benchmarks provided by proprietors. Unable to validate independently.

Compared by compression ratio and mean average error (MAE), GPGC significantly outperforms its direct competitors. Most notably, the compression ratio of GPGC is triple that of its nearest competitor GEDACS, a similar NASA algorithm for geospatial rasters. Furthermore, the average ratio is more than double the posted ratio of ECW, a proprietary format owned by Hexagon AC for their autonomous vehicle project. Note the median compression ratio for ECW has not been quantified in any peer-reviewed articles and is cited only from information that Hexagon itself provides.



This box chart only examines algorithms which could be independently tested; ECW and MrSID are not included as their proprietary encoding applications could not be used for exact comparisons. As the box plot suggests, **GPGC compresses data at a greater accuracy than any other lossy algorithm, while being comparable to the extreme compression ratios of JPEG**. Note, the wide IQR of JPEG and GPGC draws from their use of entropy coding, with each algorithm being highly sensitive to the type of data it is compressing.

Implementation

The development of this research has been funded by the international research consortium VAIL, an intercollegiate subsidiary to the NASA Armstrong Flight Research Center to implement the GPGC algorithm into a new open-source automated ground collision avoidance system for small civilian aircraft like those deployed on American fighter aircraft.

As implemented, the novel method has shown exceptional results for aircraft encoding. It benefits largely from its simplicity and reliability, with a planar system that makes it intuitive to calculate collision vectors without any additional assumptions or checks.

VAIL
Vehicle Autonomy and Intelligence Lab
Image courtesy of VAIL

Furthermore, the project is attempting to create a specification for GDAL and QGIS, the two most popular open-source applications for interacting with geospatial data, allowing data to be read, analyzed, and written with the same ease as any other format such as GeoTIFF. Finally, if possible, steps have been taken to modify GPGC slightly to allow for implicit encoding into TIFF files, making the compression extremely accessible without the need for any additional binary formats.

Conclusion

Over the large testing data set, GPGC has been shown to supersede GEDACS and ECW in compression ratio, accuracy, encoding speed, and decoding speed. Although testing was not possible for ECW and MrSID, it encodes data with an even greater efficiency than their advertised benchmarks. Furthermore, the deterministic planar encoding system ensures that there are no flagrant artifacts in the encoded rasters. As such, all of the engineering objectives have been exceeded.

- A method for partitioning the data was devised through the creation of a recursive quad-tree structure.
- Considerations of entropy allowed for intelligent encoding of raster data.
- Data was encoded in such a way that it was guaranteed to never produce artifacting.
- The quadtree structure was decoded using a novel depth-first-search algorithm specifically designed for GPGC
- The codec was evaluated compared to similar and competing algorithms.

Future Research

Possibly the most exciting part of GPGC is the massive room it still leaves for improvement. The provided implementation does its best to maximize efficiency, but several entropy coding steps were omitted from the method and could be the subject of future research. Immediately, the mosaicing system stands out as being a particularly inefficient method for allowing odd-number divisions. There is much room to allow minimal encoding strain while not also forcing data into unnecessarily small bands.

Possibly countering the inefficiency of the band solution for mosaicing, geospatial compression as described would be benefited enormously from a Huffman Coding system post-processed into the quadtree. The Huffman Code allows for more efficient encoding of structures by representing leaf nodes as pointers to another binary tree structure

GPGC
General Purpose Geospatial Compression