Integrating TEZIP into LibPressio: A Case Study of Integrating a Dynamic Application into a Static C Environment

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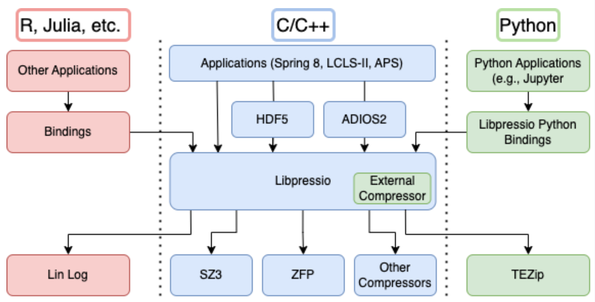
MOTIVATION

LCLS-II at SLAC, SNS at Oak Ridge Laboratory, and other instruments use software written in C and C++, producing huge volumes of time evolving data at high rate [6, 5]. Data compression can decrease the volume of data we need to move and store. TEZIP is a neural network (NN) based compressor designed for high-quality compression of time-evolving data, but TEZIP is written in Python and is not easily usable from or ported to C++ [4]. TEZIP isn't the only compressor with this challenge, such as the LinLogCompress.jl in Julia and other compressors using PyTorch/TensorFlow, e.g., Autoencoder Based Compressor [1, 3]. Bespoke C/C++ integrations for each compressor would be infeasible. **In this work we develop new components in LibPressio that allow us to integrate with TEZIP and other external compressors efficiently with a systematic approach [7]**

Figure 1: Flowchart Contextualizing the TEZIP-LibPressio Integration with other integration pathways across languages. Our contributions in green.

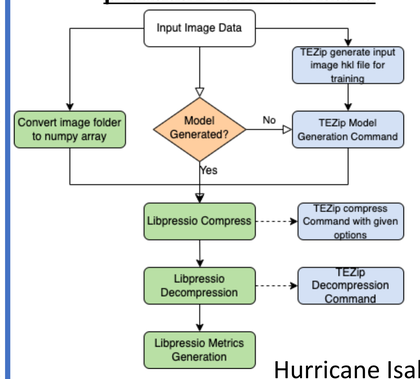


RESEARCH CHALLENGES

- TEZIP and LibPressio were designed for **different input formats** (colored images vs arrays) that need flexible and **efficient conversion** strategies
- TEZIP presents a **high startup overhead** from initialization that needs mitigation strategies.
- TEZIP was designed for **out-of-core** compression, and LibPressio for **in-core.**
- We need good strategies to **share memory** and **hide** file access **overheads** for fair comparisons.

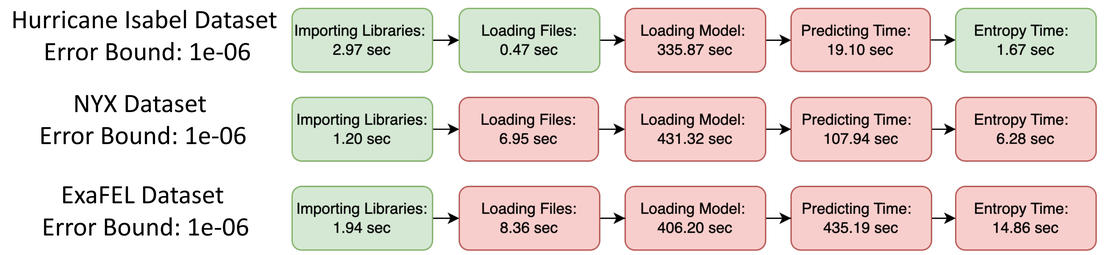
TEZIP COMPRESSION PRINCIPLES

Figure 2: Flowchart Depicting Basic Steps of TEZIP and calling protocol from LibPressio



- TEZIP is a neural network based compressor designed for time-evolving data
  - Image data is preprocessed into python objects for training and validation via hickle, which serializes to HDF5 [4]
  - Model architecture is saved in JSON format, along with the model weights in HDF5
- Similar to SZ3, TEZIP predicts the next data point based on the previous, and stores the difference (delta) between the prediction and the true next point [2]
- Unlike SZ3, TEZIP needs a **training phase** to train the Neural Network. This results in **overhead** in the form of initializing TensorFlow, the training of neural network
- Timing Profile of TEZIP compression and loading of the model shows opportunities for optimization during loading of the model, prediction, and entropy (Figure 3)

Figure 3: Flowchart Depicting Time Elapsed For Stages of TEZIP Compression



EVALUATION

Figure 4: Compressor Performance

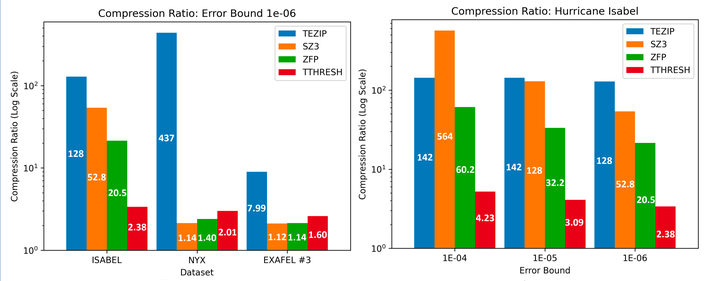


Figure 4A *Figure 4B*

Figure 5: Decompression Artifacts for SZ3 and TEZip

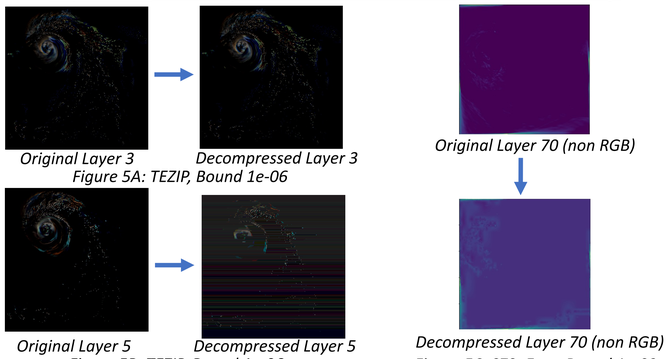


Figure 5A: TEZIP, Bound 1e-06

Figure 5B: TEZIP, Bound 1e-06

Figure 5C: SZ3, Error Bound 1e-02

Compressor Comparison Methodology

- Without this integration, comparison to other compressors would be difficult
- 4 Compressors Via LibPressio: TEZIP, SZ3, ZFP, TTHRESH
- 3 Error Bounds: 1e-04 to 1e-06, absolute error bound
- 3 Datasets from Scientific Data Reduction Benchmarks [8]
  - Hurricane ISABEL: Weather Simulation
  - NYX: Cosmological Simulation
  - ExaFEL: LCLS Serial Crystallography Image Data
- Compression Ratio And Artifact Analysis

Analysis

- Applications care about compression ratio and what artifacts are generated in the process. This integration makes an analysis possible.
- TEZIP's compression ratio for Hurricane Isabel is 128 which is **2.4** times greater than the SZ3's, 52.8 (Figure 4A).
- TEZIP: Since the neural network observes patterns and predict data, it can erroneously shadow images' most probable input for a given space. (Figure 5A, 5B)
- SZ3: Interpolation Error can result in one outlying data point creating a shadowing effect on the surrounding data (Figure 5C)

RESULTS

Basic Integration of TEZIP into LibPressio is completed

- Compression, decompression, and metric generation for TEZIP are enabled by LibPressio External Compressor Framework
- Artifacts generated during TEZIP processes shadow data using patterns found by NN

FUTURE WORK

Optimize integration to enable fair comparisons to other compressors

- Utilize Mochi to avoid start up overhead
- Utilize shared memory to avoid copies and FS overheads
- Explore the model training
  - Model training is in the "set_options" command, and is not included in the timing
- Research how to shorten the model loading and prediction time for TEZIP

CONCLUSION

- This work sets a precedent for the integration of non C/C++ compressors into LibPressio
- A similar framework can be used for other compressors in the future

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