OBNZip — Intelligent Seismic Data Compressor for OBNs

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1. Overview

Intelligent Seismic Data Compressor for OBNs (OBNZip) is an RD&I initiative of LISHA, LVA, LaSin and Petrobras sponsored by Petrobras. It aims to develop aseismic data compression algorithm encompassing embedded, server, and workstation platforms. The project focuses on data produced by **Ocean Bottom Node**s (OBNs) which includes sound pressure and accelerations. The compression algorithm explores both classical compression techniques and **Artificial Intelligence (AI)** enabled compression. The project also investigates techniques to efficiently manage the energy budget of such nodes, as well as alternative for them to communicate among themselves, underwater vehicles, and surface vessels.

2. Seismic Data Compressor

The primary objective of OBNZip is to develop an advanced system for compressing underwater seismic data collected by Ocean Bottom Nodes (OBNs) through the application of artificial intelligence techniques. In addition, the project encompasses exploratory research into submarine wireless communication and energy management strategies within OBN systems. The developed compression system is intended to enable more efficient data transmission, while the integration of AI models aims to enhance energy efficiency by facilitating the selection of optimized operational modes for the OBNs.

To address these challenges, OBNZip has been conceived as a domain-specific data compression solution, specifically tailored to the unique properties of seismic data acquired from OBN systems. The software is designed to achieve high compression efficiency, maintain computational scalability, and ensure adaptability across various hardware platforms. By preserving data fidelity while significantly reducing file sizes, OBNZip supports optimized workflows throughout the seismic data lifecycle, including acquisition, transmission, and post-processing stages. Its modular and flexible architecture allows for deployment across diverse computing environments, ranging from resource-constrained embedded systems located near the data source to high-performance computing servers used in centralized processing facilities. Performance evaluations of OBNZip are conducted across three key operational contexts: Embedded, Workstation, and Server, each corresponding to distinct phases in the processing of seismic data.

2.1. Architecture

The architecture of the OBNZip compressor is illustrated in Figure 1 and is composed of three primary components: a front-end interface, a data analysis pipeline, and a modular compression pipeline.

The front-end interface facilitates adaptation to a wide range of execution environments—including command-line interfaces on desktop systems, web-based servers in cloud environments, and APIs within embedded platforms. This component is responsible for parsing configuration files, executing commands, and dynamically constructing the compression pipeline to suit the specific operational context.

At the core lies the modular compression pipeline, designed to support a sequence of processing stages. These stages typically include transform encoding, sampling, predictive coding, dimensionality reduction, and quantization, culminating in entropy encoding. Quantization, positioned immediately prior to the entropy encoding stage, plays a crucial role in enhancing the compatibility and effectiveness of diverse compression strategies. During decompression, this stage may also facilitate signal smoothing through dequantization techniques.

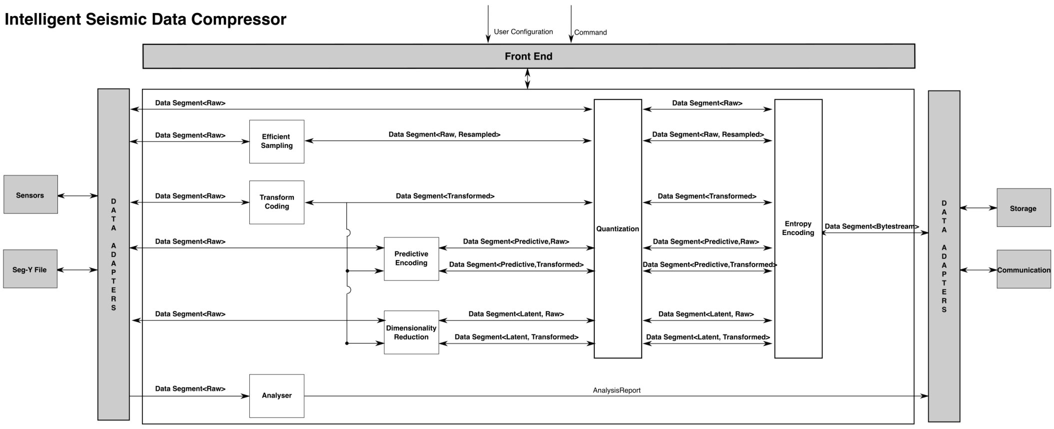

Figure 1: Compressor topview architecture.

2.2. Results for OBNZip workstation

Figures 1 show that while the GPU implementation incurs higher execution times than the CPU for small datasets—due to data transfer overhead from main to GPU memory—it consistently outperforms the CPU as the number of spatial traces exceeds approximately 700. For larger datasets, GPU execution time remains nearly constant due to its parallel processing advantages, whereas CPU time continues to increase. This trend highlights that despite initial overheads, GPUs are more efficient for larger workloads, as their computational parallelism offsets data transfer costs and delivers superior performance compared to CPUs.

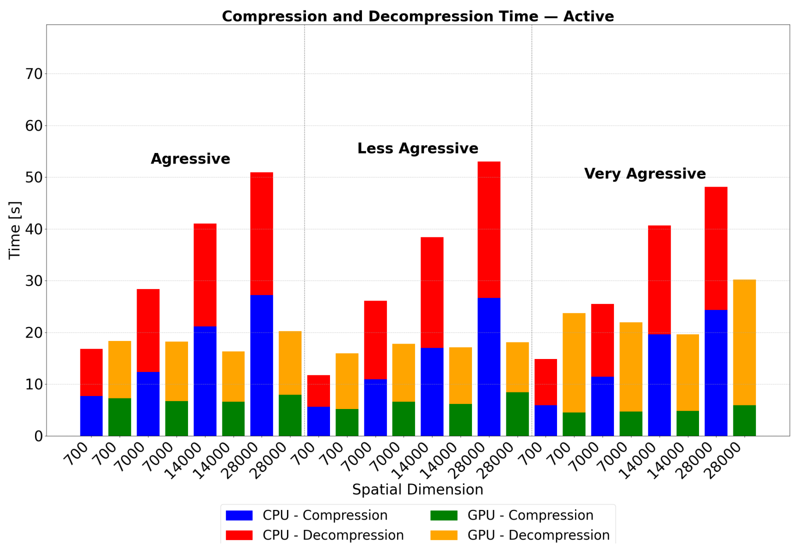

Figure 1: Compres sion and

decompression times for Active dataset using CPU and GPU implementations under various configuration settings

Figures 2 display compression ratios across varying levels of compression aggressiveness and dataset types, revealing that lower aggressiveness settings yield higher compression ratios—indicating less data reduction and larger compressed files. While "Aggressive" settings produce moderately lower ratios than "Less Aggressive" ones, the difference is relatively minor. In contrast, the "Very Aggressive" configuration leads to a pronounced decrease in compression ratio—often by 50% or more—highlighting its effectiveness in achieving significantly more compact data representations.

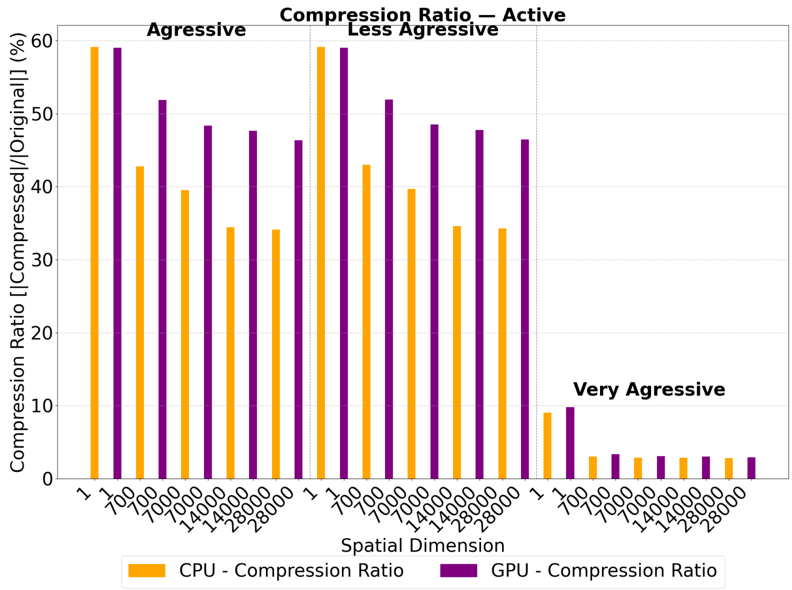

Figure 2: Compression ratio for Active dataset using CPU and GPU implementations under various configuration settings

Figures 3 show that Normalized Root Mean Squared Error (NRMSE) increases with greater compression aggressiveness, reflecting the typical trade-off between data reduction and reconstruction accuracy. While aggressive compression introduces higher error, it also achieves significantly better compression ratios, which may be acceptable depending on application needs. Notably, GPU-based compression consistently results in lower NRMSE values compared to CPU implementations—especially under "Aggressive" and "Less Aggressive" settings—indicating that the GPU not only provides speed advantages but also tends to preserve data fidelity more effectively.

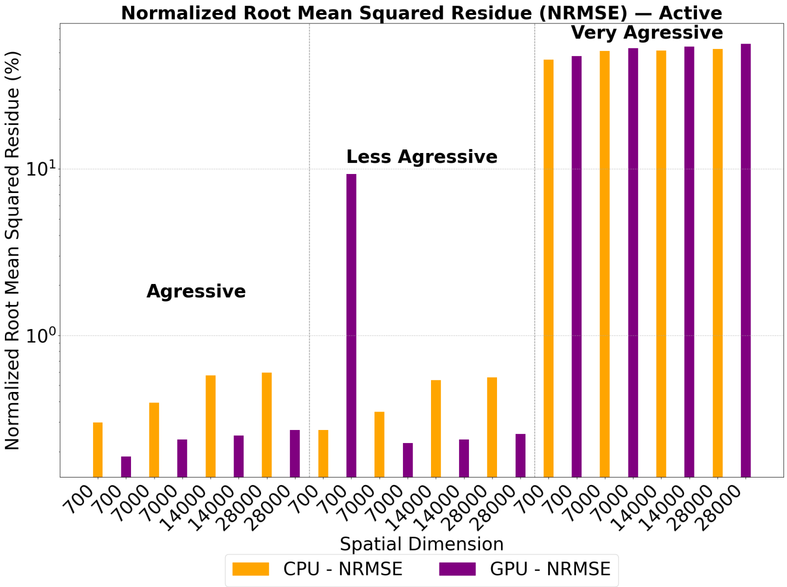

Figure 3: NRSME for Active dataset using CPU and GPU implementations under various configuration settings

3. Exploratory Studies

OBNZip project also aims to corry out exploratory studies on submarine wireless communication and energy management in OBNs, as briefly described below.

3.1. Energy Management

This objective will conduct an exploratory study on energy management in OBNs, including monitoring the energy available in the storage system, the orchestration of the operating modes of the various components of the OBN in terms of energy and recharging of storage systems. Resource scaling techniques, such as acoustic and thermal electric energy harvesting and a seawatter battery, are under development.

3.2. Underwater Communication

This exploratory study aims investigate about underwater wireless communication to determine the boundary conditions for application of the main technologies available in scenarios of interest to Petrobras, that is, deep marine waters. Two technologies are under investigation and tests: optical and acoustical communication. Experimental test have been carried out in water tanks and low cost prototypes are under development.

4. Publications

https://lisha.ufsc.br/pub/index.php?key=OBNZip