Dedispersion Algorithm Implementation Comparison

This document is a high-level comparison of various implementations of dedispersion algorithms.

This work evaluated three types of dedispersion algorithms implemented in various programming languages (Python, Julia, and CUDA):

Brute-Force

This algorithm sums along each trial dispersion curve for each time sample. This results in many redundant calculations as it is the unoptimized but straightforward implementation of dedispersion.

Theoretical Algorithmic Complexity: n_freq * n_time * n_trials

Fast Dispersion Measure Transform (FDMT)

This algorithm reduces redundant computations by recursively processing two sub-bands of the data.

Algorithmic complexity: max{n_time * n_trials * log2(n_freq), 2 * n_freq *n_time}

Original paper: https://arxiv.org/pdf/1411.5373.pdf

Taylor-Tree

This algorithm regularizes the problem to then exploit redundant computation between trial DMs.

Algorithmic complexity: n_time * n_freq * log2(n_freq)

Specific Implementations Evaluated:

CPU FDMT in Python (pyfdmt)

Codebase: https://bitbucket.org/vmorello/pyfdmt/src/master/

CPU FDMT in Julia (FastDMTransform.jl)

Codebase: https://github.com/max-Hawkins/FastDMTransform.jl Note: This fork is used to test against a single-threaded FDMT implementation that's a more fair comparison to pyfdmt.

GPU FDMT in Python (from Bifrost)

Codebase: https://github.com/ledatelescope/bifrost

CPU Brute-Force Dedispersion in Julia (Dedisp.jl)

Codebase: https://github.com/max-Hawkins/Dedisp.jl Note: This fork is used to remove the loop vectorization helper to make a more fair comparison. Kiran Shila is the primary author of Dedisp.jl.

GPU Brute-Force Dedispersion in Julia (Dedisp.jl)

Codebase: https://github.com/max-Hawkins/Dedisp.jl Note: This fork is used to remove the normalization step after dedispersion. Kiran Shila is the primary author of Dedisp.jl.

Why??? - How is this relevant to Breakthrough Listen or SETI technosignature searches?

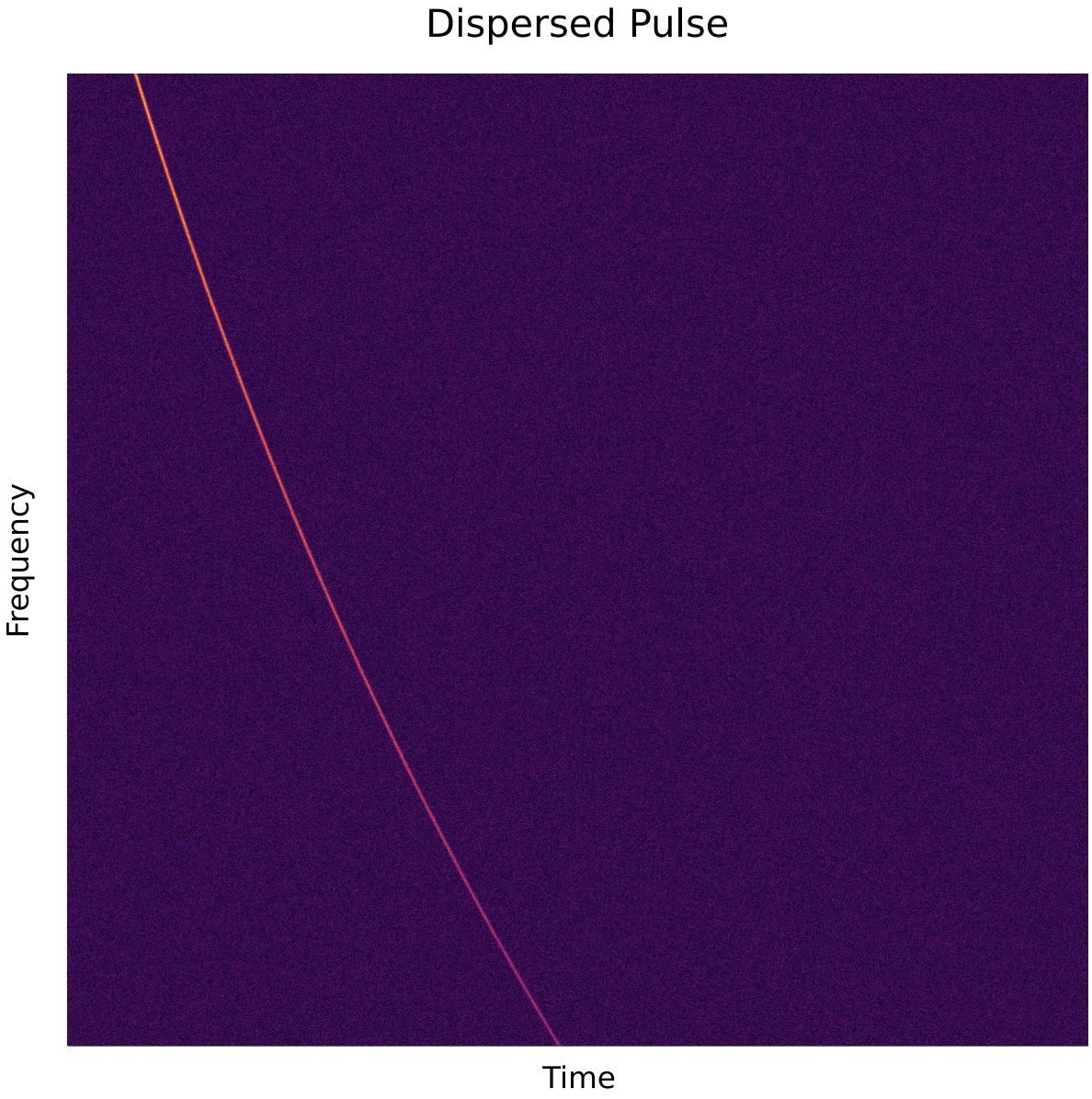
These dedispersion are very much of interest to Breakthrough Listen. With minor tweaks to the algorithms, **all of these implementations can be applied to linear-drifting signals.** FDMT is especially easy to reimplement because it takes a parameter for the frequency-dependent time delay. The others are somewhat harder, but in theory, all of these algorithms are directly applicable to doppler searches.

Benchmarking these results allows us to focus our reimplementation efforts into the most promising algorithms for use in doppler search pipelines. This work is necessary because **the current dedoppler algorithms are NOT performant enough to run on our future real-time commensal pipeline setups.**

Test Input Data

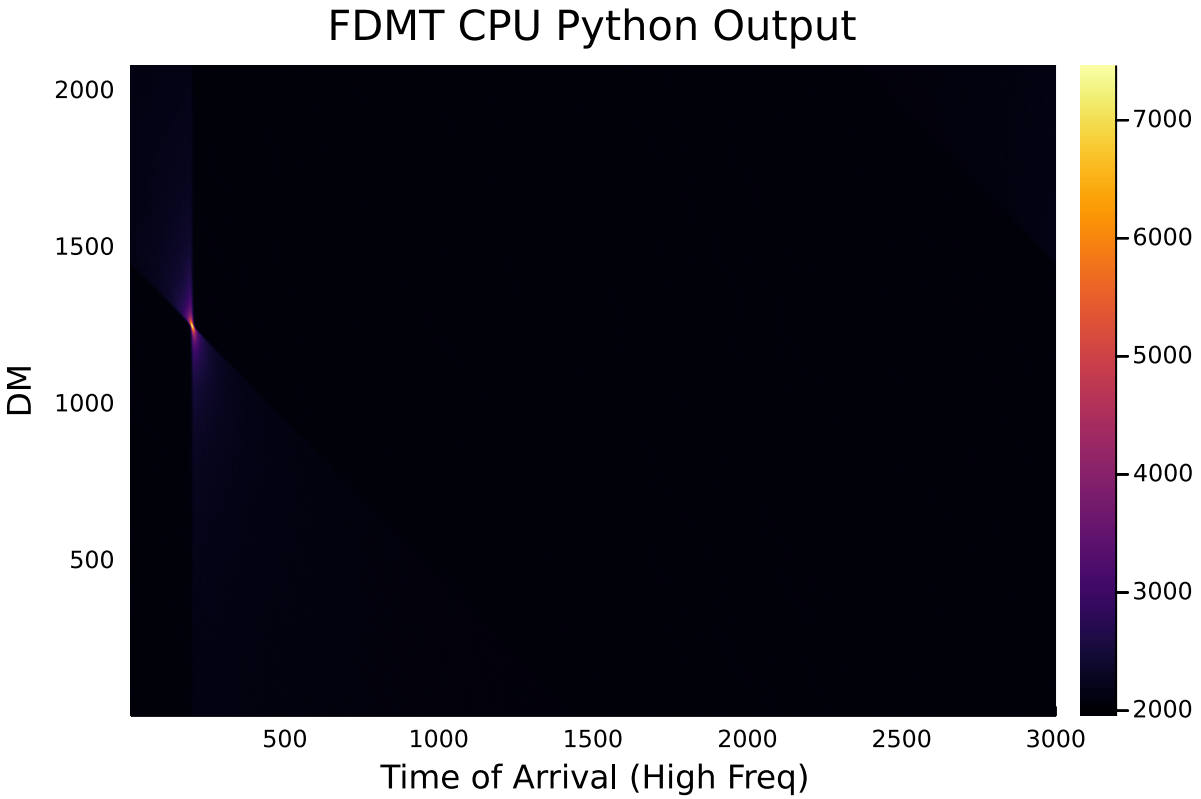
This is the test dispersed pulse used for evaluation and benchmarking. This is the only input data used for this stage of comparison since we want to retool these algorithms to dedoppler linear-drifting signals before making more rigorous comparisons.

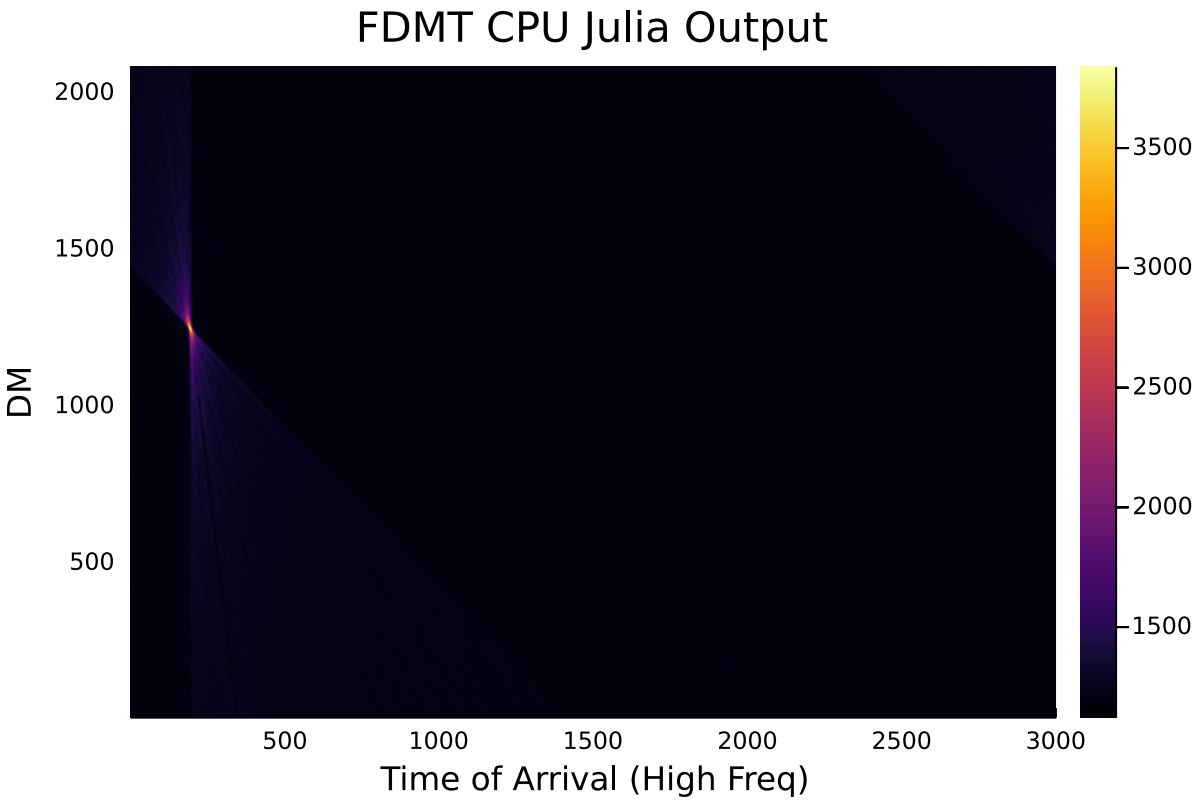
The input data size is 3000 time samples with 4096 frequency channels. For all of the implementations, 2076 unique DM trials were tested from 0 to 2000. Data transfer times between the CPU<->GPU were not counted for GPU implementations. The intent is to compare the calculation time alone, but later considerations will take GPU idiosyncracies into account.

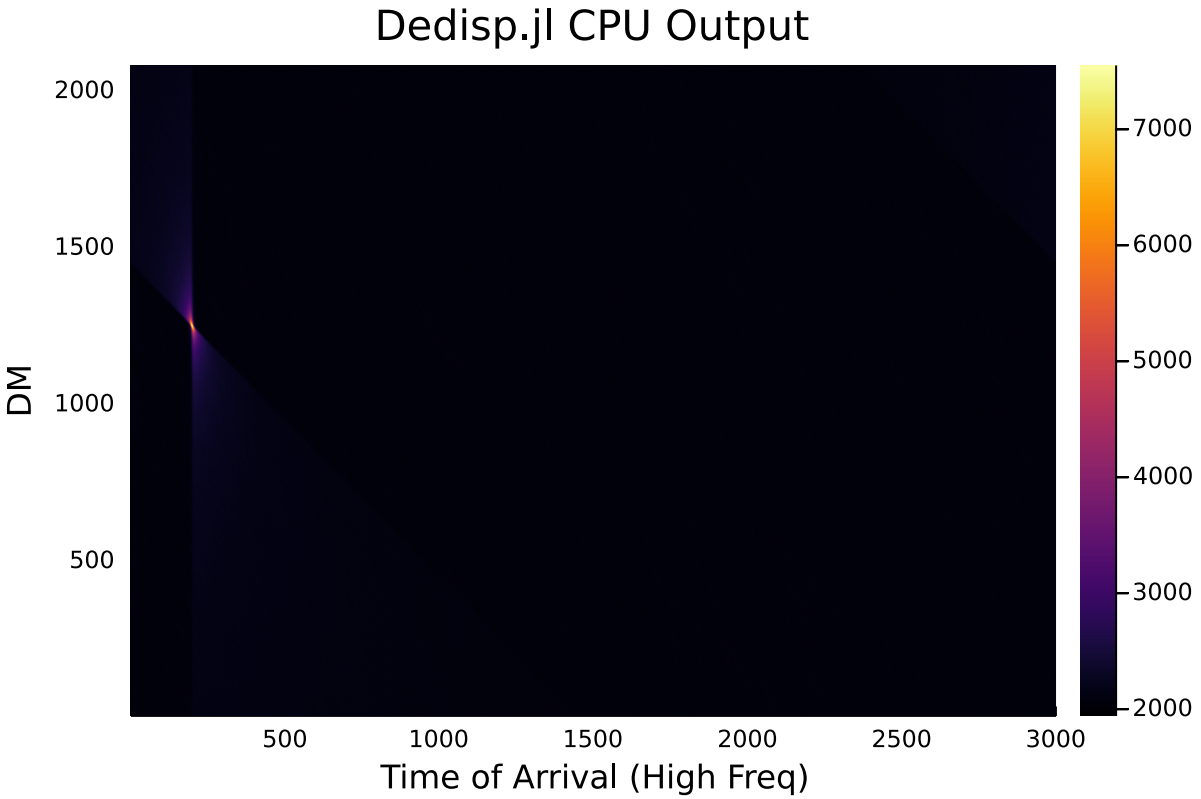


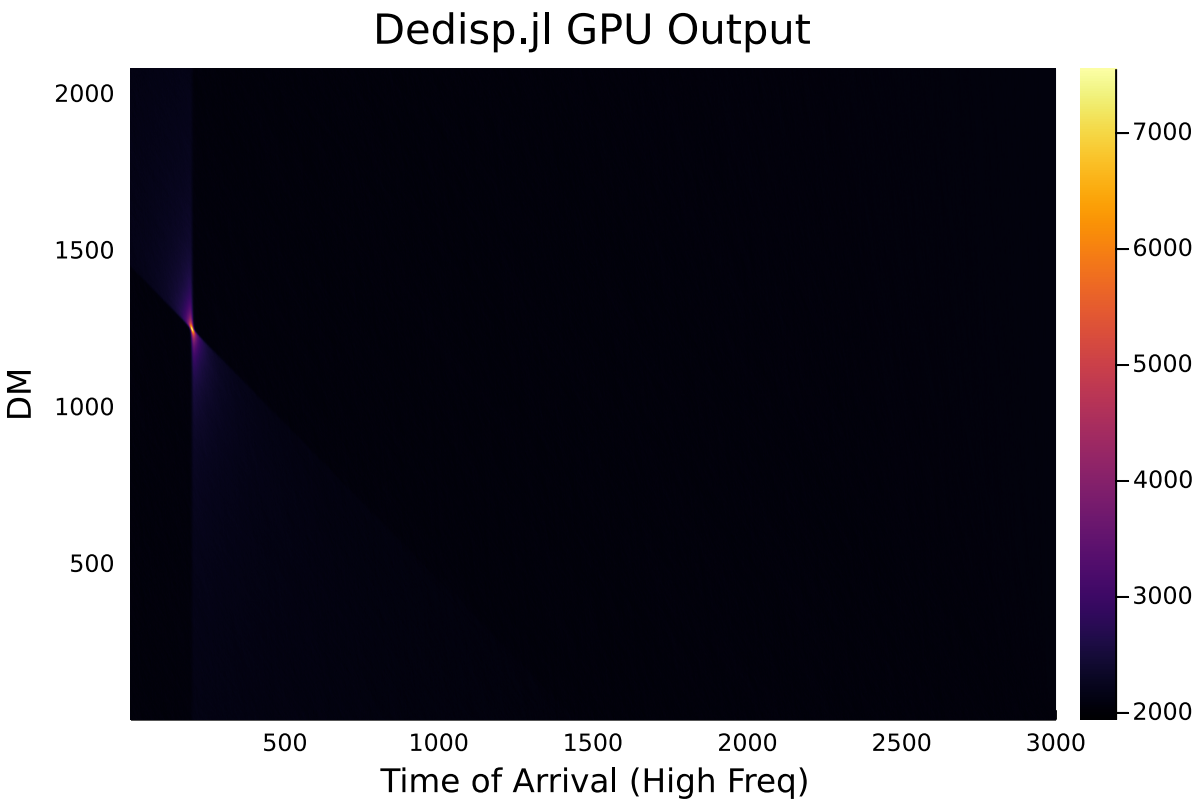
Output Verification

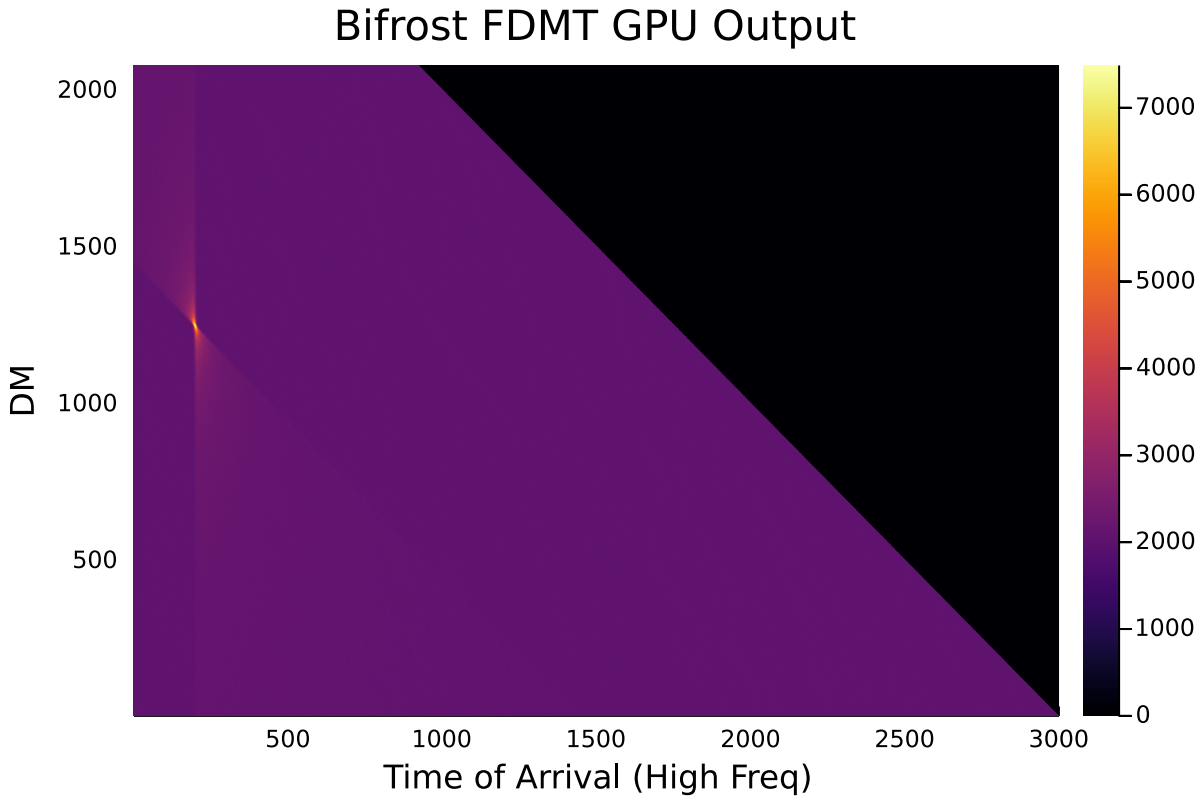
First, the above test data was fed through all the implementations and then their corresponding outputs were plotted below. A fair comparison requires that we first ensure that all the algorithms are doing roughly the same thing.


FDMT CPU Python Output
DM
2000
1500
1000
500
500
1000
1500
2000
2500
3000
Time of Arrival (High Freq)
7000
6000
5000
4000
3000
2000


FDMT CPU Julia Output
DM
2000
1500
1000
500
500
1000
1500
2000
2500
3000
Time of Arrival (High Freq)
3500
3000
2500
2000
1500


Dedisp.jl CPU Output
DM
2000
1500
1000
500
500
1000
1500
2000
2500
3000
Time of Arrival (High Freq)
7000
6000
5000
4000
3000
2000


Dedisp.jl GPU Output
DM
2000
1500
1000
500
500
1000
1500
2000
2500
3000
Time of Arrival (High Freq)
7000
6000
5000
4000
3000
2000



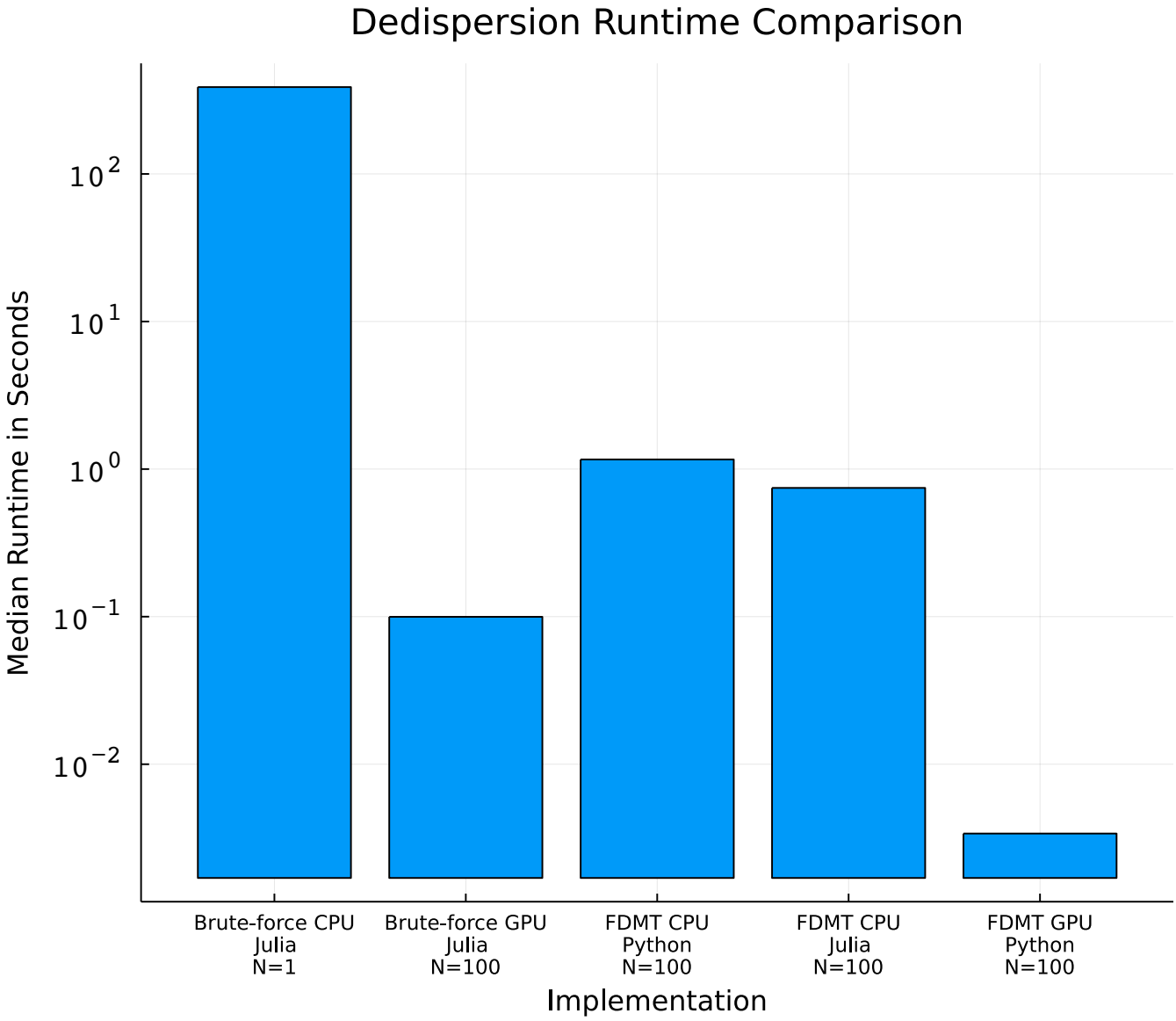
As you can see, the outputs visually are very similar. These results, along with some numerical verification steps were enough to allow us to proceed with the benchmarks.

The only discrepancies are found in the FDMT CPU Julia and the FDMT GPU implementations. The CPU Julia version's discrepancies are more than just a scaling factor, but since the GPU versions were of primary interest in this evaluation, we didn't spend much time looking into this. The FDMT GPU implementation's output matches the others except for the upper right triangle which is filled with zeros. This is because these values are filled with 'garbage' data in the other implementations, and in a real-world processing scenario should be thrown-out or overlapped with the next block of data. The data is garbage because the DM curve wraps past the extent of the current block.

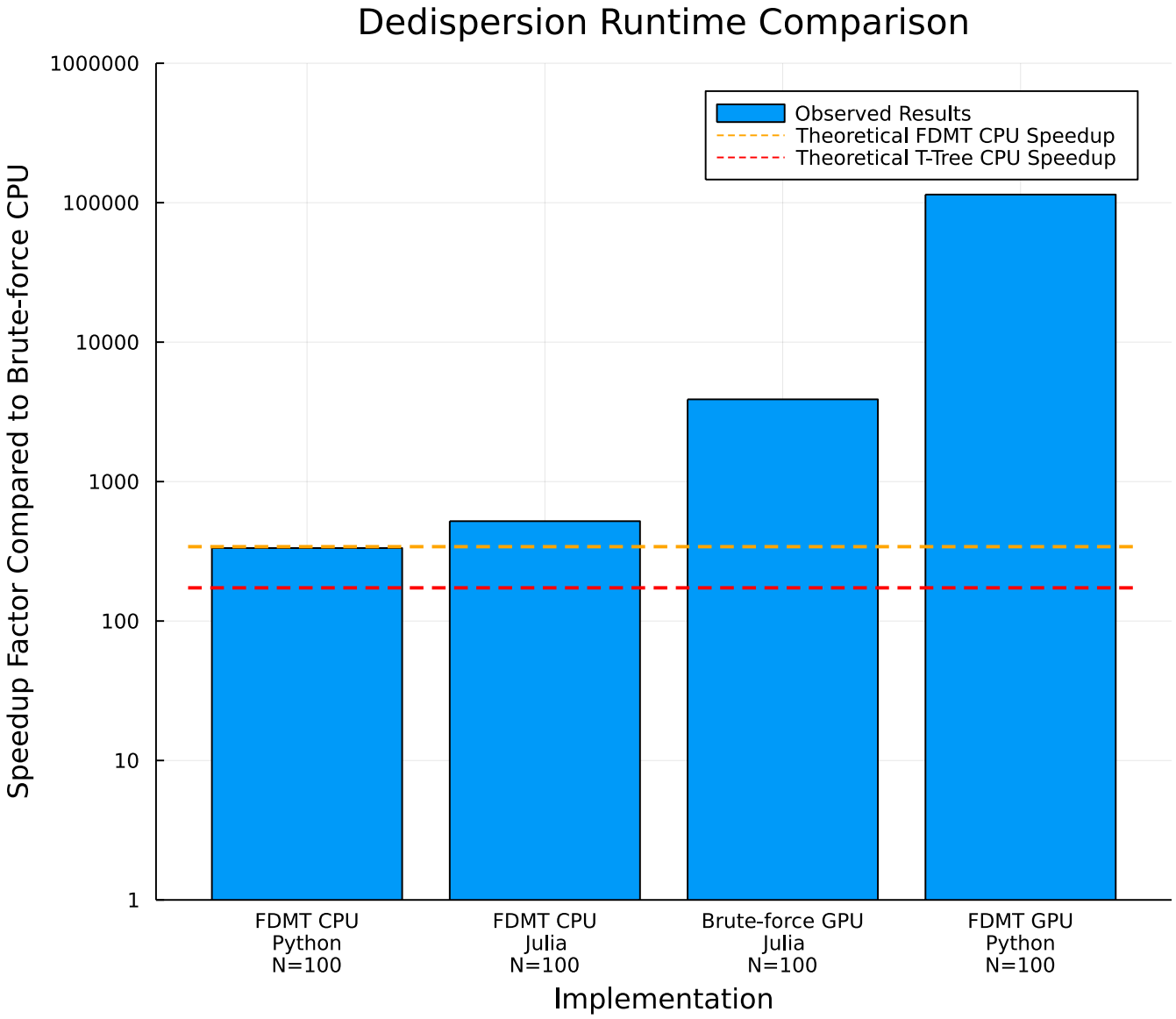
Runtime Comparisons

Once the outputs were verified, each algorithm was run N times while recording the runtime for each trial.

The following benchmark data were collected on Breakthrough Listen's blpc1 server using a Titan Xp GPU. If you have additional questions about the setup for these benchmarks, contact Max Hawkins. All benchmarks should be taken with some grains of salt, but the intent of this project was to evaluate the general nature and performance of existing dedoppler implementations. Relative order of magnitude comparisons are what we aimed for.



GPU-acceleration and the FDMT algorithms gave drastic speedups. These results match the expected behavior based on algorithmic complexity analysis and the parallel nature of GPUs.



Here, all runtimes were graphed relative to the slowest implementation (brute-force CPU). As you can see, the Python CPU FDMT implementation speedup almost exactly matches the expected theoretical algorithmic complexity speedup. The Julia implementation is higher than expected likely due to compiler tricks, vectorized instructions, or a highly inefficient brute-force CPU implementation.

Conclusion

For future dedispersion algorithm reimplementation for doppler search pipelines, the FDMT GPU algorithm should be the implementation of focus.

Future Work

In the future, we'd like to also evaluate the performance of the following implementations (primarily Fourier domain dedispersion) as the literature and exterior benchmarks show favorably even against the GPU FDMT implementation from this study:

GPU Brute-Force Dedispersion in C/C++ (Dedisp library)

Codebase: https://github.com/kiranshila/dedisp

GPU Fourier Domain Dedispersion in C/C++ (Dedisp library)

Codebase: https://github.com/kiranshila/dedisp

July 1st, 2022 - Max Hawkins and Kevin Jordan with help from Dave MacMahon, Daniel Czech, and Kiran Shila (CalTech)