

Dear Dr. István Reguly,

Thank you very much for your thoughtful and detailed review of my dissertation. I truly appreciate the time and effort you took to engage with my work, and I am grateful for your constructive feedback. I have carefully considered your comments and suggestions, and I address each of them individually below.

1. In multiple occasions, the performance of the tridiagonal solver appears to be a bottleneck, and as demonstrated it does not utilize the device well (far from the roofline). Is this an inherent limitation of the way tridiagonal equations can be solved in parallel, or how cuSPARSE is used in your case?

As shown in Table 4-4, in the GPU implementation of MEMD, the percentage of overall execution time attributed to the tridiagonal solver decreases as the signal length increases. With longer signals, the custom kernel functions begin to dominate the overall execution time. The longest signal length presented in Table 4-4 is approximately 100k, equivalent to less than one minute of data at a sampling rate of 2048 Hz. However, EEG recordings in practical experimental settings are typically much longer. Consequently, the relative contribution of the tridiagonal solver to total execution time would decrease even further in practical scenarios. Although the solver does not fully utilize the device (far from the roofline), it no longer constitutes a primary performance bottleneck.

kernel	sample size						
	4097	8193	16385	32769	43009	79873	104449
<i>pcrGlobalMemKernel_manyRhs</i>	50.0%	47.6%	42.3%	35.5%	31.4%	23.0%	20.2%
<i>pcrLastStageKernel_manyRhs</i>	14.9%	12.1%	9.5%	7.2%	6.1%	4.4%	3.5%
<i>pcrGlobalMemKernelFirstPass_manyRhs</i>	12.5%	10.2%	7.9%	5.9%	5.0%	3.3%	2.8%
<i>crGlobalForIterations_multiple</i>	0.0%	0.0%	3.6%	4.5%	5.4%	5.9%	5.6%
<i>crGlobalBottomKernel_multiple</i>	0.0%	2.2%	3.3%	3.8%	6.8%	8.9%	9.1%
<i>prescan_arbitrary</i>	5.3%	4.5%	3.7%	2.9%	2.5%	1.8%	1.6%
<i>prescan_large</i>	3.8%	3.2%	2.7%	2.2%	1.9%	1.5%	1.3%
<i>interpolate</i>	2.8%	4.9%	8.1%	12.7%	14.5%	19.4%	21.7%
<i>add</i>	4.9%	4.1%	3.3%	2.5%	2.2%	1.6%	1.4%
<i>averageUppperLower</i>	0.8%	1.3%	2.0%	2.9%	3.3%	4.3%	4.7%
<i>tridiagonal_setup</i>	0.8%	1.2%	1.8%	2.7%	3.2%	4.1%	4.4%
<i>spline_coefficients</i>	0.7%	1.1%	1.8%	2.6%	3.1%	3.9%	4.3%
<i>select_extrema_max</i>	0.5%	0.8%	1.3%	2.3%	2.6%	3.4%	3.7%
<i>select_extrema_min</i>	0.5%	0.8%	1.3%	2.3%	2.6%	3.4%	3.7%
<b>tridiagonal solver kernels</b>	<b>77.3%</b>	<b>72.0%</b>	<b>66.6%</b>	<b>56.8%</b>	<b>54.7%</b>	<b>45.5%</b>	<b>41.2%</b>
<b>custom kernels</b>	<b>20.1%</b>	<b>21.9%</b>	<b>26.0%</b>	<b>33.1%</b>	<b>35.9%</b>	<b>43.3%</b>	<b>46.7%</b>

Table 4-4: Relative contributions of the kernels to the overall execution time for different signal lengths.

The cuSPARSE library function `cusparseSgtsv2_nopivot()` used in my implementation uses a combination of Cyclic Reduction (CR) and Parallel Cyclic Reduction (PCR) algorithms to efficiently solve tridiagonal systems and is highly optimized for performance. Nevertheless, implementing a custom tridiagonal solver using kernel functions may still offer advantages, such as increased flexibility or the potential for kernel fusion to further optimize memory access and execution flow.

2. You refer to ICA-dependent pipelines as semi-automatic. Do you think there are sufficient

samples available to train a machine learning model to perform artifact identification?

Several automatic artifact labeling tools based on machine learning models or spatio-temporal features—such as ICLabel [1], MARA [2], and ADJUST [3]—are publicly available and have been integrated into the EEGLAB environment. Compared to the computational cost of performing ICA decomposition, the artifact labeling of independent components is negligible in terms of processing time. The ultimate goal of the proposed tensor core-based ICA implementation is to be integrated into the EEGLAB/MATLAB environment, enabling the decomposition results to be directly passed to these automatic labeling tools. This integration would contribute to a significantly faster and fully automatic EEG processing pipeline.

#### References:

- [1] L. Pion-Tonachini, K. Kreutz-Delgado, and S. Makeig, “ICLabel: An automated electroencephalographic independent component classifier, dataset, and website,” *Neuroimage*, vol. 198, pp. 181–197, Sep. 2019, doi: 10.1016/J.NEUROIMAGE.2019.05.026.
- [2] I. Winkler, S. Haufe, and M. Tangermann, “Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals,” *Behavioral and Brain Functions*, vol. 7, no. 1, pp. 1–15, Aug. 2011, doi: 10.1186/1744-9081-7-30/FIGURES/9.
- [3] A. Mogron, J. Jovicich, L. Bruzzone, and M. Buiatti, “ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features,” *Psychophysiology*, vol. 48, no. 2, pp. 229–240, Feb. 2011, doi: 10.1111/J.1469-8986.2010.01061.X,.

Once again, I would like to express my sincere gratitude for your valuable feedback and constructive suggestions, which have greatly helped improve the quality of my dissertation.

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