

# Parallel Implementation of Multivariate Empirical Mode Decomposition on GPU

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N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," Proc. R. Soc. A Math. Phys. Eng. Sci., vol. 454, no. 1971, pp. 903–995, 1998

#### 1.2 Features of EMD and its variants





#### multidimensional space curve Stop iterating **Multivariate** The number of extremes of 2 Project along direction vectors envelope 1.5 each projected signal < 3 1. 0.5 Generate the envelopes of the 0 -0.5 projected signals -1 , Identify extremes of each projected signals -1.5 -2 \_ Calculate mean envelope with -2.5 Project along direction vectors multivariate envelopes Residue = curve – mean envelopes Curve – IMF Direction vector channel, Does Residue meet IMF conditions?

MEMD process flowchart

Envelopes of projected signals and the multivariate envelope

#### 1.3 Processing pipeline of MEMD

#### 2.1 Numerical steps of MEMD

1. Use the data matrix to dot product the direct vector:



2. Detect the extreme points on the projection signal

Maxima			Minima		
	p1			p1	
	p2			p2	
	р3			р3	
	p4			p4	
	р5			р5	
	p6			p6	
	р7			р7	
	p8			p8	



#### 2.1 Numerical steps of MEMD

3. Find the corresponding multivariate extrema





4. Interpolate on the dimensions of multivariate extrema





(Here we need to perform six interpolation operations)

#### 2.1 Numerical steps of MEMD

5. Calculate multivariate mean envelope





6. Calculates the mean envelope from the mean envelopes of all direction vectors.

#### 2.2 Implementation details

Use CUDA shuffle operation to detect extrema





#### 2.2 Implementation details

Use prefix sum to get compact extrema vector



#### 2.2 Implementation details

Multi tridiagonal systems solver in interpolation





#### 2.3 Data layout in memory





#### 3.1 Performance overview

Dataset: EEGLAB sample dataset Number of channels: 4 Number of direction vectors: 64 Length of signal: 30504

Number of IMFs: 8 Number of iteration: 10

Execution time (in log scale) 1000 Execution time (milliseconds) 100 Compared to CPU, 10 Titan achieved **190X** RTX3070 achieved 55X speedup 0.1 0.01 0.001 TitanXP RTX3070Laptop i7-9700k (MATLAB)



#### 3.2 Kernel performance compared to literature



Number of channels: 16 Number of direction vectors: 64 Length of signal: 1001

Number of IMFs: 8 Number of iteration: 10

	Execution time (µs)				
Kernels	Number of calls	Literature [1]	Our version	Speedup	
HammersleySeqGen	1	11	3.42	3x	
DirectionVecGen	1	148	64.64	2x	
Projections	7	802	10.21	79x	
PeaksDetection	70	1232	6.61	187x	
BoundaryCondSet	140	3961	84.73	47x	
EnvelopeMean	140	152	28.34	5x	

[1] Mujahid, T., Rahman, A. U., & Khan, M. M. (2017). GPU-Accelerated Multivariate Empirical Mode Decomposition for Massive Neural Data Processing. *IEEE Access*, *5*, 8691–8701.

#### 4 Future works



- 1. There are still limitations in our performance tests, and in the future, we will test more datasets including 128-channel EEG signals under different execution parameters.
- 2. The effects of some detailed parameter settings on the decomposition results still need to be further studied, such as the settings of extrema and tridiagonal matrix boundary conditions, and the setting of sifting stop criterion.
- 3. Some numerical validations are currently ongoing, and the stream mechanism will be introduced into MEDM computations to further improve the parallelization and performance.