





High performance GPU accelerated MuST software

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i≘ README.md				
Must T				
<i>MuST</i> (<i>Mu</i> ltiple Scatterin petascale and beyond co	ig T heory) is an ab initio electronic structure calculat Imputing capability, for the first principles study of q	tion software suite, with uantum phenomena in		

disordered materials. It is capable of performing

KKR for ordered structures

- KKR-CPA for random structures (with/without short range chemical order)
- LSMS calculations for large systems
- Kubo-Greenwood method for residual resistivity calculation
- ...and many more upcoming features!

This repository is actively developed and maintained - please check for regular updates!

docs passing license BSD-3-Clause MuST Wiki MuST Youtube Channel

User Guide

All the relevant information and instructions are provided in the documentation

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- Green's function approach (KKR method)
- Locally Self-consistent Multiple Scattering (LSMS) method
- Computational challenge: matrix inverse
- GPU acceleration: code review
- Benchmark systems and results
- Run GPU accelerated MuST on Bridges-2 @ PSC
- Outlook

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Quantum Mechanical Approach to Solid State Materials



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The Self-consistent Process in an Ab Initio Electronic Structure Calculation



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Schrodinger Eq. Green's function

Free particle:
$$\hat{H}_0 | \varphi \rangle = \mathsf{E} | \varphi \rangle$$
 $\hat{G}_0 = (E - \hat{H}_0)^{-1}$

Particle in one atom site potential V: $(\hat{H}_0 + V)|\psi\rangle = E |\psi\rangle$ $\hat{G} = (E - \hat{H}_0 - V)^{-1}$

Wave-function is obtainable: $|\psi\rangle = (I + \hat{G}V)|\varphi\rangle$ \implies Charge density $|\psi\rangle = (I + \hat{G}_0T)|\varphi\rangle$ T: single site scattering matrix **Obtain charge density without wave-function :**

Green's function definition:
$$G(r, r'; E) = \sum_{n} \frac{\langle r|n \rangle \langle n|r' \rangle}{E - E_n + i\eta}$$

Density is
$$\rho(r) = -\frac{2}{\pi} Im \int_{-\infty}^{E_F} G(r,r;E) dE$$

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Multi-site case

Green's function:

$$G(\mathbf{r}_n, \mathbf{r}_n; \epsilon) = \sum_{L,L'} Z_L^n(\mathbf{r}_n; \epsilon) \tau_{LL'}^{nn}(\epsilon) Z_{L'}^{n*}(\mathbf{r}_n; \epsilon) - \sum_L Z_L^n(\mathbf{r}_n; \epsilon) J_L^{n*}(\mathbf{r}_n; \epsilon)$$

Dyson equation: $\underline{\tau}(E) = \left[\underline{t}^{-1}(E) - \underline{g}_0(E)\right]^{-1}$

$$\tau \text{-matrix: } \underline{\tau}^{nn}(\varepsilon) = \begin{bmatrix} \underline{t}_{1}^{-1}(\varepsilon) & -\underline{g}_{12}(\varepsilon) & \cdots & -\underline{g}_{1N}(\varepsilon) \\ -\underline{g}_{21}(\varepsilon) & \underline{t}_{2}^{-1}(\varepsilon) & \cdots & -\underline{g}_{2N}(\varepsilon) \\ \vdots & \vdots & \ddots & \vdots \\ -\underline{g}_{N1}(\varepsilon) & -\underline{g}_{N2}(\varepsilon) & \cdots & \underline{t}_{N}^{-1}(\varepsilon) \end{bmatrix}_{nn}^{-1}$$

Matrix rank is: 1, no spin: $N(l_{max} + 1)^2$ 2, spin: $2N(l_{max} + 1)^2$

- 1. No pseudopotentials required
- 2. No wave-function normalization and orthogonalization
- 3. No Hamiltonian diagonalization
- 4. Can be used to study random alloys (combining with CPA)

Brief summary on KKR method:

1. Solve single-site solution Z and J. single-site scattering matrix (t) and free particle propagator (g0).

- 2. Build KKR matrix.
- 3. Invert KKR matrix, obtain multiple-scattering matrix (\tau)
- 4. Construct Green's function with \tau, Z and J
- 5. Obtain charge density through Green's function
- 6. Obtain effective potential through charge density (LDA or GGA)
- 7. Go to DFT self-consistent

The Self-consistent Process in the Green function based *Ab initio* Electronic Structure Calculation



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Matrix inverse multi-core acceleration

Solving X: $A\vec{X} = \vec{B}$ through LU decomposition: 1, A = LU $2, LU\vec{X} = \vec{B}$ $3, L\vec{Y} = \vec{B}$ $4, U\vec{X} = \vec{Y}$ Intel MKL threads many-core acceleration ratio:

3.48X

Solving X:
$$\begin{bmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{bmatrix} \begin{bmatrix} X_{00} & X_{01} \\ X_{10} & X_{11} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
 is:
Solving
$$\begin{bmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{bmatrix} \begin{bmatrix} X_{00} \\ X_{10} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$
 and
$$\begin{bmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{bmatrix} \begin{bmatrix} X_{01} \\ X_{11} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

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Offloading matrix inverse on GPUs

$$G(\mathbf{r}_n, \mathbf{r}_n; \epsilon) = \sum_{L,L'} Z_L^n(\mathbf{r}_n; \epsilon) \tau_{LL'}^{nn}(\epsilon) Z_{L'}^{n*}(\mathbf{r}_n; \epsilon) - \sum_L Z_L^n(\mathbf{r}_n; \epsilon) J_L^{n*}(\mathbf{r}_n; \epsilon)$$

Block LU on CPU: N^2

Full inverse: N^3 However much faster on GPU

Recursive Block Inverse Technique

Since the LSMS method requires only the first diagonal block of the inverse matrix, we perform block inverse recursively:

$$\begin{bmatrix} \underline{A}_{11} & \underline{A}_{12} \\ \underline{A}_{21} & \underline{A}_{22} \end{bmatrix}^{-1} = \begin{bmatrix} \underline{A}_{11} - \underline{A}_{12} \underline{A}_{22}^{-1} \underline{A}_{21} \end{bmatrix}^{-1} \\ & \downarrow \\ \\ -\underline{A}_{12} \underline{A}_{22}^{-1} \underline{A}_{21} \end{bmatrix}^{-1} = \begin{bmatrix} \underline{B}_{11} & \underline{B}_{12} \\ \underline{B}_{21} & \underline{B}_{22} \end{bmatrix}^{-1} = \begin{bmatrix} \underline{B}_{11} - \underline{B}_{12} \underline{B}_{22}^{-1} \underline{B}_{21} \end{bmatrix}^{-1} \\ & \downarrow \\ \\ \\ \end{matrix}$$

The block size is a performance tuning parameter

 \underline{A}_{11}

Performance of LSMS is dominated by double complex matrix matrix multiplication © Pittsburgh Supercomputing Center, All Rights Reserved (**zgemm** in BLAS)

Offloading matrix inverse on GPUs (Code structure)



Fortran:

subroutine a(x1)
double complex:: x1(*)
call matrix_inverse_cuda(x1)
end subroutine a

CUDA in C:

```
extern "C"
```

void matrix_inverse_cuda_(double complex *x1)

cudaMalloc; cudaMemcpy(..., HostToDevice); cusolverDnZgetrf; *#LU decomposition* cusolverDnZgetrs; *#solve linear equation* cudaMemcpy(..., DeviceToHost); cudaFree;

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GPU systems

GPUs support double precision (FP64) : NVIDIA V100, A100; AMD Instinct ...

1. Lonestar6 @ TACC



2. Bridges2 @ PSC



3. BIL cluster @ PSC



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Acceleration ratio on one computing node

Testing Case: NiAu alloy totally 64 atoms; KKR matrix size: 12450 x 12450



Acceleration ratio

NiAu spin-canted (on PSC-BIL 8-A100-80G)	GPU number/MPI rank number	8	16	32	MPI rank number	
	2	5528(0 101)	4543(0 108)		(=CPU core number)	
		3320(0.101)	1313(0.100)	999(0.117) = 0599(0.124)	32	19002
	4	4618(0.104)	3022(0.117)	2589(0.134)	64	11069
	8	3790(0.194)	2452(0.129)	1821(0.148)	128	5695

- DFT basics
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Setting up environments on Bridges-2

GPU nodes

Bridges-2's GPU nodes provide exceptional performance and scalability for deep learning and accelerated computing, with a total of 40, 960 CUDA cores and 5,120 tensor cores. Bridges' GPU-AI resources have been migrated to Bridges-2, adding the DGX-2 and nine more V100 GPU nodes to Bridges-2's GPU resources.

GPU nodes			
Number	24	9	1
GPUs per node	8 NVIDIA Tesla V100-32GB SXM2	8 NVIDIA V100-16GB	16 NVIDIA Volta V100-32GB
GPU memory	32 GB per GPU 256GB total/node	16GB per GPU 128GB total/node	32GB per GPU 512GB total
GPU performance	1 Pf/s tensor		
CPUs	2 Intel Xeon Gold 6248 "Cascade Lake" CPUs 20 cores per CPU, 40 cores per node 2.50 – 3.90 GHz	2 Intel Xeon Gold 6148 CPUs 20 cores per CPU , 40 cores per node 2.4 – 3.7 GHz	2 Intel Xeon Platinum 8168 24 cores per CPU, 48 cores total 2.7 – 3.7 GHz
RAM	512GB, DDR4-2933	192 GB, DDR4-2666	1.5 TB, DDR4-2666

Setting up environments:

1. MPI:

module load openmpi/4.1.1gcc8.3.1

2. CUDA runtime: module load cuda/11.7.1

3. Intel MKL: module load mkl/2020.4.304

Download, compile and run

1. Download the latest code:

"git clone https://github.com/mstsuite/MuST.git"

2. Compile: demo architecture file at : "architecture/Bridges2-linux-gnu-mkl-cuda"

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1. Download the latest code:

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2. Compile:

demo architecture file at : "architecture/Bridges2-linux-gnu-mkl-cuda"

```
# Acceleration = 1: enable GPU acceleration
# Acceleration = 0: otherwise
#______
Acceleration = 1
# Library paths and elements, e.g.,
   HDF5_PATH = /opt/packages/HDF5/hdf5-1.10.5/PGI
   LIBXC_PATH = /opt/packages/LibXC/libxc-4.3.4/PGI
   ACCEL_PATH = /usr/local/cuda
   FFTW_PATH = /usr/local/FFTW/fftw-3.3.8/PGI
   P3DFFT_PATH = /opt/packages/P3DFFT/p3dfft-2.7.9/PGI
   LUA_PATH = /opt/packages/Lua/lua-5.3.5/PGI
# If LUA_PATH, LIBXC_PATH, FFTW_PATH, and/or P3DFFT_PATH are empty, the
# corresponding packages will be installed under $(EXTERN_LIB PATH)
MATH_PATH = /opt/intel/compilers_and_libraries/linux/mkl/
HDF5_PATH =
ACCEL
         = CUDA
ACCEL_PATH = /opt/packages/cuda/v11.7.1/
LIBXC_PATH = /jet/home/liangstein/libxc
FFTW_PATH = /jet/home/liangstein/intel_fftw_scalapack/fftw3
P3DFFT_PATH = /jet/home/liangstein/intel_fftw_scalapack/p3dfft
LUA_PATH =
LIBS
        += -L$(MATH_PATH)/lib/intel64 -lmkl_intel_lp64 -lmkl_sequential -lmkl_core -ldl -lpthread -lm '
          -lmkl_scalapack_lp64 -lmkl_cdft_core -lmkl_blacs_openmpi_lp64 \
          -L$(ACCEL_PATH)/lib64 -lcudart -lcuda -lcublas -lstdc++ -lcusolver
ADD_LIBS += -lgfortran
# Compiler tools
#_____
CC
         = mpicc
СХХ
         = mpicxx
F77
         = mpif90
FC
         = mpif90
MPICC
         = mpicc
ACCEL_CXX = nvcc -arch=sm_60
         = ar -r
```

Download, compile and run

3. A demo for GPU acceleration at location:

"Benchmark/CoCrFeMnNi/MT/u56_CUDA"

Submission example:

"sbatch -p GPU -t 48:0:0 -n 40 --gpus=v100-32:8 bash_script.sh"

In bash_script.sh:

#!/bin/bash
mpirun -n 40 ~/bind_MPI_to_GPU.sh ~/mst2_cuda < i_mst</pre>

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- 1. Build KKR matrix on GPU, reduce data transfer time
- 2. Multi-GPU matrix inverse, enable larger unit cell size
- 3. Other types of acceleration cards
- 4. Full potential calculation speed up

Thanks for your attention