Exploring a multi-resolution GPU programming model for Chapel

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A multi-resolution GPU programming model for Chapel

MOTIVATION
GPUs are a common source of performance improvement in HPC

Source: https://www.top500.org/statistics/list/
GPU Programming in Chapel

- Chapel’s multi-resolution concept
  - Start with writing “forall” loops (on CPU, proof-of-concept)
    ```chapel
    forall i in 1..n {
    ... }```
  - Apply automatic GPU code generators [1][2] when/where possible
  - Consider using the GPUIterator module [3] (Mason-registry)
  - Consider writing GPU kernels using CUDA/HIP/OpenCL or other accelerator language, and invoke them from Chapel

Example: STREAM (Original)

```
1 var A: [1..n] real(32);
2 var B: [1..n] real(32);
3 var C: [1..n] real(32);
4 // STREAM
5 forall i in 1..n {
6   A(i) = B(i) + alpha * C(i);
7 }
```
Example:
STREAM (C interoperability)

- Invoking CUDA/HIP/OpenCL code using the C interoperability feature

```c
1 extern proc GPUST(A: [] real(32), 1 // separate C file
2     B: [] real(32), 2 void GPUST(float *A,
3     C: [] real(32), 3 float *B,
4     al: real(32), 4 float *C,
5     lo: int, hi: int); 5 float al,
6 var A: [1..n] real(32); 6 int start,
7 var B: [1..n] real(32); 7 int end) {
8 var C: [1..n] real(32); 8 // CUDA/HIP/
9 // Invoking CUDA/OpenCL program 9 // OpenCL Code
10 GPUST(A, B, C, alpha, 1, n); 10 }
```
Example: STREAM (GPUIterator)

- Connecting the GPU version with the forall loop using the GPUIterator module

```java
1 // GPU Iterator (in-between)
2 var G = lambda (lo: int, hi: int,
3   nElems: int) {
4   GPUST(A, B, C, alpha, 1, n);
5 };
6 var CPUPercent = 50;
7 forall i in GPU(1..n, G, CPUPercent) {
8   A(i) = B(i) + alpha * C(i);
9 }

// separate C file
1 // separate C file
2 void GPUST(float *A,
3   float *B,
4   float *C,
5   float al,
6   int start,
7   int end) {
8   // CUDA/HIP/
9   // OpenCL Code
10 }
```

Note: the GPUIterator is designed to facilitate
1) hybrid execution (CPUs+GPUs), and 2) distributed execution
Example:
No appropriate GPU abstraction

Highest-level Chapel-GPU Programming

```chapel
forall i in 1..n {
    A(i) = B(i) + alpha * C(i);
}
```

Lowest-level Chapel-GPU Programming

```
// separate C file
__global__ void stream(float *dA, float *dB, float *dC, float alpha, int N) {
    int id = blockIdx.x * blockDim.x + threadIdx.x;
    if (id < N) {
        dA[id] = dB[id] + alpha * dC[id];
    }
}
```

Research Question:
What is an appropriate and portable programming interface that bridges the ”forall” and GPU versions?
Contributions:
- Design and implementation of “MID”/”LOW-MID” levels Chapel GPU API
- Performance evaluations on different distributed and single-node platforms (Summit, Cori, and a single-node AMD machine)
A multi-resolution GPU programming model for Chapel

DESIGN
An overview of the LOW-MID/MID GPU API for Chapel

Note: Multi-locales plus multi-GPUs execution can be easily done with the GPUIterator module.
Chapel GPU API Design:

Summary

- **Use case:**
  - The user would like to 1) write GPU kernels, or 2) utilize highly-tuned GPU libraries, and would like to stick with Chapel for the other parts (allocation, data transfers)

- **Provides two levels of GPU API**
  - LOW-MID: Provides wrapper functions for raw GPU APIs
    - Example: `var ga: c_void_ptr = GPUAPI.Malloc(sizeInBytes);`
  - MID: Provides more user-friendly APIs
    - Example: `var ga = new GPUArray(A);`

- **Important design decisions**
  - The user is still supposed to write kernels in CUDA/HIP/OpenCL
  - The APIs significantly facilitates the orchestration of:
    - Device memory (de)allocation, and host-to-device/device-to-host data transfers,
    - The use of the APIs does not involve any modifications to the Chapel compiler
Chapel GPU API Design: LOW-MID GPU API

Summary
- Provides the same functionality as CUDA/HIP/OpenCL
- The user is still supposed to write CUDA/HIP/OpenCL kernels
- The user is supposed to handle both C types and Chapel types

Key APIs
- Device Memory Allocation
  - `Malloc(ref devPtr: c_void_ptr, size: size_t);`
- Host-to-device, and device-to-host data transfers
  - `Memcpy(dst: c_void_ptr, src: c_void_ptr, count: size_t, direction: int);`
- Ensuring the completion of GPU computations
  - `DeviceSynchronize(void);`
- Device Memory deallocation
  - `Free(c_void_ptr);`
Chapel GPU API Design: MID GPU API

- **Summary**
  - More natural to Chapel programmers
  - The user is still supposed to write CUDA/HIP/OpenCL kernels

- **Key APIs**
  - Device Memory Allocation
    - `var dA = new GPUArray(A);`
  - Host-to-device, and device-to-host data transfers
    - `ToDevice(dA:GPUArray, ...); FromDevice(dA: GPUArray, ...);`
    - `dAToDevice(); dA.fromDevice();`
  - Device Memory deallocation
    - `Free(dA:GPUArray, ...);`
    - `dA.Free();`
Chapel GPU API Design:
LOW-MID/MID GPU API Example

<table>
<thead>
<tr>
<th>LOW-MID Level</th>
<th>MID-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  use GPUAPI;</td>
<td>1 use GPUAPI;</td>
</tr>
<tr>
<td>2  var A: [1..n] real(32);</td>
<td>2 var A: [1..n] real(32);</td>
</tr>
<tr>
<td>3  var B: [1..n] real(32);</td>
<td>3 var B: [1..n] real(32);</td>
</tr>
<tr>
<td>4  var C: [1..n] real(32);</td>
<td>4 var C: [1..n] real(32);</td>
</tr>
<tr>
<td>5  var dA, dB, dC: c_void_ptr;</td>
<td>5 var dA = new GPUArray(A);</td>
</tr>
<tr>
<td>6  var size: size_t =</td>
<td>6 var dB = new GPUArray(B);</td>
</tr>
<tr>
<td>7    (A.size:size_t * c_sizeof(A.eltType));</td>
<td>7 var dC = new GPUArray(C);</td>
</tr>
<tr>
<td>8   Malloc(dA, size);</td>
<td>8 toDevice(dB, dC);</td>
</tr>
<tr>
<td>9   Malloc(dB, size);</td>
<td>9 LaunchST(dA.dPtr(), dB.dPtr(),</td>
</tr>
<tr>
<td>10  Malloc(dC, size);</td>
<td>dC.dPtr(), alpha,</td>
</tr>
<tr>
<td>11  Memcpy(dB, c_ptrTo(B), size, TODEVICE);</td>
<td>dN: size_t);</td>
</tr>
<tr>
<td>12  Memcpy(dC, c_ptrTo(C), size, TODEVICE);</td>
<td>10 DeviceSynchronize();</td>
</tr>
<tr>
<td>13  LaunchST(dA, dB, dC, alpha, N: size_t);</td>
<td>11 FromDevice(dA);</td>
</tr>
<tr>
<td>14  DeviceSynchronize();</td>
<td>12 Free(dA, dB, dC);</td>
</tr>
<tr>
<td>15  Memcpy(c_ptrTo(A), dA, size, FROMDEVICE);</td>
<td></td>
</tr>
</tbody>
</table>
Example: Single-node execution of STREAM (MID-level w/ GPUUlterator)

```
1  var A: [1..n] real(32);
2  var B: [1..n] real(32);
3  var C: [1..n] real(32);
4  var GPUCallBack = lambda (lo: int, hi: int, nElems: int) {
5      var dA = new GPUArray(A);
6      var dB = new GPUArray(B);
7      var dC = new GPUArray(C);
8      toDevice(dB, dC);
9      LaunchST(dA.dPtr(), dB.dPtr(),
10             dC.dPtr(), alpha,
11             dN: size_t);
12      DeviceSynchronize();
13      FromDevice(dA);
14      Free(dA, dB, dC);
15  };
16  forall i in GPU(1..n, GPUCallBack, CPUPercent) {
17      A(i) = B(i) + alpha * C(i);
18  }
```

The user has the option of writing a device function(s), a device lambda(s), or a library call(s)

```
1  // separate C file (CUDA w/ device lambda)
2  void LaunchST(float *dA, float *dB,
3                 float *dC, float alpha, int N) {
4      GPU_FUNCTOR(N, 1024, NULL,
5                  [=] __device__ (int i) {
6                      dA[i] = dB[i] + alpha * dC[i];
7                  });
8  }
```
Example: Distributed execution of STREAM (MID-level w/ GPUIterator)

```java
var D: domain(1) dmapped Block(boundingBox={1..n}) = {1..n};
var A: [D] real(32);
var B: [D] real(32);
var C: [D] real(32);
var GPUCallBack = lambda (lo: int, hi: int, nElems: int) {
  var dA = new GPUArray(A.localSlice(lo..hi));
  var dB = new GPUArray(B.localSlice(lo..hi));
  var dC = new GPUArray(C.localSlice(lo..hi));
  toDevice(dB, dC);
  LaunchST(dA.dPtr(), dB.dPtr(),
           dC.dPtr(), alpha,
           dN: size_t);
  DeviceSynchronize();
  FromDevice(dA);
  Free(dA, dB, dC);
};
forall i in GPU(D, GPUCallBack,
                 CPUPercent) {
  A(i) = B(i) + alpha * C(i);
}
```

The user has the option of writing a device function(s), a device lambda(s), or a library call(s)
A multi-resolution GPU programming model for Chapel

IMPLEMENTATION
Implementation of GPU API

- Provides an external module (GPUAPI)
  - Can be used either stand-alone or with the GPUIterator module
  - [https://github.com/ahayashi/chapel-gpu](https://github.com/ahayashi/chapel-gpu)
    - The “feature/explicit” branch
- Currently supports NVIDIA and ROCM-ready AMD GPUs

Diagram:
- LOW-MID and MID API
  - GPUAPI.chpl
  - GPUAPI.cu
  - nvcc
  - Binary for NVIDIA GPUs
  - hipify
  - hipcc
  - Binary for AMD GPUs
A multi-resolution GPU programming model for Chapel

PERFORMANCE EVALUATIONS
Performance Evaluations

- Platforms
  - Cori GPU@NERSC: Intel Xeon (Skylake) + NVIDIA V100 GPU
  - Summit@ORNL: IBM POWER9 + NVIDIA Tesla V100 GPU
  - A single-node AMD machine: Ryzen9 3900 + Radeon RX570

- Chapel Compilers & Options
  - Chapel Compiler 1.20.0 with the --fast option

- GPU Compilers
  - CUDA: NVCC 10.2 (Cori), 10.1 (Summit) with the -O3 option
  - AMD: ROCM 2.9.6, HIPCC 2.8 with the -O3 option
Performance Evaluations (Cont’d)

- Tasking & Multi-locale execution
  - CHPL_TASK=qthreads
  - CHPL_COMM=gasnet
  - CHPL_COMM_SUBSTRATE=ibv

- GPUIterator (For distributed GPU execution)
  - https://github.com/ahayashi/chapel-gpu/tree/feature/explicit

- Applications
  - Stream
  - BlackScholes
  - Matrix Multiplicaiton
  - Logistic Regression
  - Source code can be found at:
    https://github.com/ahayashi/chapel-gpu/tree/feature/explicit/apps
How many lines are added/modified?

<table>
<thead>
<tr>
<th></th>
<th>LOC Baseline (Chapel LOW + CUDA)</th>
<th>LOC LOW-MID (Chapel LOW-MID + CUDA)</th>
<th>LOC MID (Chapel MID + CUDA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stream</td>
<td>4 + 24 = 28</td>
<td>16 + 9 = 25</td>
<td>11 + 9 = 20</td>
</tr>
<tr>
<td>BlackScholes</td>
<td>4 + 99 = 103</td>
<td>16 + 83 = 99</td>
<td>11 + 83 = 94</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>2 + 36 = 38</td>
<td>16 + 18 = 34</td>
<td>10 + 18 = 28</td>
</tr>
<tr>
<td>Matrix Multiplication</td>
<td>3 + 30 = 33</td>
<td>14 + 15 = 29</td>
<td>10 + 16 = 26</td>
</tr>
</tbody>
</table>

The use of GPU API decreases LOC.
How fast are GPUs? (Multi-nodes, 1GPU/node, Cori)

- Each app shows good strong scalability
- No significant performance difference between L (LOW), LM (LOW-MID), and M (MID)

Data Size: \( n = 2^{30} \) (Stream, BlackScholes)

4096x4096 (MM) \( n \)Features = \( 2^{18} \), \( n \)Samples = \( 2^{4} \)
How fast are GPUs?
(Multi-nodes, 1GPU/node, Summit)

- Each app shows good strong scalability
- No significant performance difference between L (LOW), LM (LOW-MID), and M (MID)

Data Size: $n = 2^{30}$ (Stream, BlackScholes)

4096x4096 (MM) $n$Features = $2^{18}$, $n$Samples = $2^{4}$
How fast are GPUs?
(Multi-nodes, 6GPUs/node, Cori, Summit)

BlackScholes, MID-level, $n = 2^{30}$

<table>
<thead>
<tr>
<th>Speedup over 1GPU (1node)</th>
<th>1 GPU</th>
<th>6 GPUs</th>
<th>2 GPUs</th>
<th>12 GPUs</th>
<th>4 GPUs</th>
<th>24 GPUs</th>
<th>8 GPUs</th>
<th>48 GPUs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 node</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>24</td>
<td>48</td>
<td>1</td>
</tr>
<tr>
<td>2 nodes</td>
<td>2</td>
<td>6</td>
<td>12</td>
<td>24</td>
<td>48</td>
<td>24</td>
<td>48</td>
<td>1</td>
</tr>
<tr>
<td>4 nodes</td>
<td>4</td>
<td>6</td>
<td>12</td>
<td>24</td>
<td>48</td>
<td>24</td>
<td>48</td>
<td>1</td>
</tr>
<tr>
<td>8 nodes</td>
<td>8</td>
<td>6</td>
<td>12</td>
<td>24</td>
<td>48</td>
<td>24</td>
<td>48</td>
<td>1</td>
</tr>
</tbody>
</table>

Cori

Summit
How fast are GPUs?
(A single-node, Ryzen9 + Radeon RX570)

The GPUAPI works on an AMD GPU machine
A multi-resolution GPU programming model for Chapel

CONCLUSIONS & FUTURE WORK
Conclusions

Summary
- The GPUAPI provides an appropriate interface between Chapel and accelerator programs
  - Source code is available (the feature/explicit branch):
    - https://github.com/ahayashi/chapel-gpu
- The LOW-MID and MID level GPU API enable a higher-level GPU programming interface w/ minimal performance overhead
  - Verified on NVIDIA and AMD GPUs
- The GPUAPI + the GPUIterator module facilitate distributed GPU programming using Chapel
  - Verified on Summit and Cori
  - The use of GPUs can significantly improve the performance of Chapel programs
Future Work

- Building a higher-level programming model
  - Built on top of the MID-level API
  - $\forall i \in D$ with (in: B, out: A) {...}
    \[
    \Rightarrow \quad \text{var } dA = \text{GPUArray}(A); \text{var } dB = \text{GPUArray}(B); \text{toDevice}(B); \text{kernel}(); \text{fromDevice}(A);
    \]
  - For the kernel code generation, will explore the possibility of avoiding/minimizing compiler modifications
    - e.g., generate a C/C++ loop + OpenMP/OpenACC/Other pragma
      - Chapel's Vectorizing Iterator does a similar thing (vectorizeOnly())

- Asynchronous GPU API + Futures
Future work (Cont’d)

Wish List: lambda + capture by reference

Current MID-level

<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>use GPUAPI;</td>
</tr>
<tr>
<td>2</td>
<td>var A: [1..n] real(32);</td>
</tr>
<tr>
<td>3</td>
<td>var B: [1..n] real(32);</td>
</tr>
<tr>
<td>4</td>
<td>var dA = new GPUArray(A);</td>
</tr>
<tr>
<td>5</td>
<td>var dB = new GPUArray(B);</td>
</tr>
<tr>
<td>6</td>
<td>toDevice(dB);</td>
</tr>
<tr>
<td>7</td>
<td>LaunchVC(dA.dPtr(), dB.dPtr(), N: size_t);</td>
</tr>
<tr>
<td>8</td>
<td>DeviceSynchronize();</td>
</tr>
<tr>
<td>9</td>
<td>FromDevice(dA);</td>
</tr>
<tr>
<td>10</td>
<td>Free(dA, dB);</td>
</tr>
</tbody>
</table>

If dA, dB, N can be captured...

<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<tr>
<td>4</td>
<td>var dA = new GPUArray(A);</td>
</tr>
<tr>
<td>5</td>
<td>var dB = new GPUArray(B);</td>
</tr>
<tr>
<td>6</td>
<td>var in = (dB); // tuple</td>
</tr>
<tr>
<td>7</td>
<td>var out = (dA); // tuple</td>
</tr>
<tr>
<td>8</td>
<td>Launch (in, out, lambda () {</td>
</tr>
<tr>
<td>9</td>
<td>LaunchVC(dA.dPtr(), dB.dPtr(), N: size_t);</td>
</tr>
<tr>
<td>10</td>
<td>});</td>
</tr>
</tbody>
</table>

```
Thank you for your attention!
Any questions?
Backup Slides
Chapel’s iterator

Chapel’s iterator allows us to control over the scheduling of the loops in a productive manner.

```
// Iterator over fibonacci numbers
forall i in fib(10) {
    A(i) = B(i);
}
```

<table>
<thead>
<tr>
<th>CPU1</th>
<th>0</th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU2</td>
<td>5</td>
<td>8</td>
<td>13</td>
<td>21</td>
<td>34</td>
</tr>
</tbody>
</table>

https://chapel-lang.org/docs/master/primers/parIters.html
The GPUIterator automates work distribution across CPUs+GPUs

```
forall i in 1..n {
  A(i) = B(i);
}
```

```
forall i in GPU(1..n, GPUWrapper, CPUPercent) {
  A(i) = B(i);
}
```

CPU Portion

```
        1         n
CPU1    CPU2    ..........    CPUm
```

GPUPercent = 100 - CPUPercent

```
        1         n
CPU1    CPU2    ..........    CPUm
```

```
        1         n
GPU1    ..........    GPUk
```
How to use the GPUIterator?

```plaintext
var GPUCallBack = lambda (lo: int, hi: int, nElems: int){
    assert(hi-lo+1 == nElems);
    GPUVC(A, B, lo, hi);
};
forall i in GPU(1..n, GPUCallBack, CPUPercent){
    A(i) = B(i);
}
```

This callback function is called after the GPUIterator has computed the subspace (lo/hi: lower/upper bound, n: # of elements)

GPU() internally divides the original iteration space for CPUs and GPUs

Tip: declaring CPUPercent as a command-line override ("config const") helps us to explore different CPU+GPU executions
The GPUIterator supports Zippered-forall

```plaintext
forall (_, a, b) in zip(GPU(1..n, ...), A, B) {
  a = b;
}
```

- Restriction
  - The GPUIterator must be the leader iterator

The GPUIterator supports Distributed Arrays (Cont’d)

- No additional modifications for supporting multi-locales executions

<table>
<thead>
<tr>
<th>Locale 0</th>
<th>A(x)</th>
<th>......</th>
<th>A(y)</th>
<th>Locale 1</th>
<th>A(z)</th>
<th>......</th>
<th>A(w)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU Portion</td>
<td>GPU Portion</td>
<td>CPU Portion</td>
<td>GPU Portion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A (Chapel)</td>
<td>1</td>
<td>A.localeSlice(lo..hi)</td>
<td>A.localeSlice(lo..hi)</td>
<td>n</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: localeSlice is Chapel’s array API
Implementation of the GPUIterator

```cpp
coforall subloc in 0..1 {
    if (subloc == 0) {
        const numTasks = here.getChild(0).maxTaskPar;
        coforall tid in 0..#numTasks {
            const myIters = computeChunk(...);
            for i in myIters do
                yield i;
        }
    } else if (subloc == 1) {
        GPUCallBack(...);
    }
}
```
How fast are GPUs?
(Single-node, POWER8 + K80)

- The iterator enables exploring different CPU+GPU strategies with very low overheads
- The GPU is up to 145x faster than the CPU, but is slower than the GPU due to data transfer costs in some cases
How fast are GPUs?
(Single-node, Xeon + M2050)

![Speedup over original forall](chart.png)

- The iterator enables exploring different CPU+GPU strategies with very low overheads.
- The GPU is up to 126x faster than the CPU, but is slower than the GPU due to data transfer costs in some cases.
How fast are GPUs compared to Chapel’s BLAS module on CPUs?
(Single-node, Core i5 + Titan Xp)

Motivation: to verify how fast the GPU variants are compared to a highly-tuned Chapel-CPU variant

Result: the GPU variants are mostly faster than OpenBLAS’s gemm (4 core CPUs)
When is hybrid execution beneficial? (Single node, Core i7+UHD)

With tightly-coupled GPUs, hybrid execution is more beneficial