Streaming and Nested Parallelism in Accelerate

Robert Clifton-Everest University of New South Wales

Jointly with

Frederik M. Madsen Trevor L. McDonell Manuel M. T. Chakravarty Gabriele Keller



- Lots of raw computing power
 - This one: 2688 cores @ 867 MHz



- Lots of raw computing power
 - This one: 2688 cores @ 867 MHz
- Different hardware design
 - Limited instruction set
 - SIMD: Cores run the same program, but on different data



- Lots of raw computing power
 - This one: 2688 cores @ 867 MHz
- Different hardware design
 - Limited instruction set
 - SIMD: Cores run the same program, but on different data
- How can we take advantage of this power?



- Lots of raw computing power
 - This one: 2688 cores @ 867 MHz
- Different hardware design
 - Limited instruction set
 - SIMD: Cores run the same program, but on different data
- How can we take advantage of this power?

With a high-level embedded language of course!



An embedded language for GPU programming



An embedded language for GPU programming



dotp xs ys =





zipWith (*) xs ys





```
Embedded
language arrays
                              From Accelerate library
  dotp xs ys = fold (+) 0 ( zipWith (*) xs ys )
                                   #include <accelerate cuda.h>
                                    typedef DIM1 DimOut;
                                   extern "C" __global__ void zipWith
                                    (
                                       const DIM1 shIn0,
                                       const Int64* restrict arrIn0 a0,
                                       const DIM1 shIn1,
                                       const Int64* __restrict__ arrIn1_a0,
                                       const DIM1 shOut,
                                       Int64* __restrict__ arrOut a0
                                    )
                                    {
                                       const int shapeSize = size(shOut);
                                       const int gridSize = blockDim.x * gridDim.x;
                                       int ix;
                                       for (ix = blockDim.x * blockIdx.x + threadIdx.x; ix < shapeSize; ix += gridSize) {</pre>
                                          const DimOut sh = fromIndex(shOut, ix);
                                          const int v0 = toIndex(shIn0, shape(sh));
                                          const int v1 = toIndex(shIn1, shape(sh));
                                          arrOut_a0[ix] = arrIn0_a0[v0] * arrIn1_a0[v1];
```



• A deep embedding

• A deep embedding

dotp :: Acc (Vector Float) -> Acc (Vector Float) -> Acc (Scalar Float)
dotp xs ys = fold (+) 0 (zipWith (*) xs ys)

• A deep embedding

type Vector e = Array (Z:.Int) e dotp :: Acc (Vector Float) -> Acc (Vector Float) -> Acc (Scalar Float) dotp xs ys = fold (+) 0 (zipWith (*) xs ys)

• A deep embedding



• A deep embedding



A deep embedding





Mandelbrot fractal



Mandelbrot fractal



n-body gravitational simulation



Mandelbrot fractal



n-body gravitational simulation



Canny edge detection



stable fluid flow

n-body gravitational simulation



Canny edge detection



stable fluid flow

n-body gravitational simulation

d6b821d937a4170b3c4f8ad93495575d: saitek1 d0e52829bf7962ee0aa90550ffdcccaa: laura1230 494a8204b800c41b2da763f9bbbcc462: lina03 d8ff07c52a95b30800809758f84ce28c: Jenny10 e81bed02faa9892f8360c705241191ae: carmen89 46f7d75718029de99dd81fd907034bc9: mellon22 0dd3c176cf34486ec00b526b6920b782: helena04 9351c4bc8c8ba17b58d5a6a1f839f356: 85548554 9c36c5599f40d08f874559ac824d091a: 585123456 4b4dce6c91b429e8360aa65f97342e90: 5678go 3aa561d4c17d9d58443fc15d10cc86ae: momo55

Recovered 150/1000 (15.00 %) digests in 59.45 s, 185.03 MHash/sec

Password "recovery" (MD5 dictionary attack)



Canny edge detection

- Matrix-vector multiplication.
- In terms of dotp?

- Matrix-vector multiplication.
- In terms of dotp?

- Matrix-vector multiplication.
- In terms of dotp?




What's missing?

• Matrix-vector multiplication.



Which of the following frontend features would help you make better use of Accelerate or enable you to use Accelerate?



Accelerate as a standalone (non-embedded) DSL	20	12%
Irregular data structures (e.g., quad-trees, oct-trees)	50	29%
Nested parallelism (e.g., map of map, map of fold, etc)	69	41%
Sparse data structures (e.g., sparse matrices)	64	38%
Support for graph processing	42	25%

Which of the following frontend features would help you make better use of Accelerate or enable you to use Accelerate?



Accelerate as a standalone (non-embedded) DSL	20	12%
Irregular data structures (e.g., quad-trees, oct-trees)	50	29%
Nested parallelism (e.g., map of map, map of fold, etc)	69	41%
Sparse data structures (e.g., sparse matrices)	64	38%
Support for graph processing	42	25%

Which of the following frontend features would help you make better use of Accelerate or enable you to use Accelerate?



Accelerate as a standalone (non-embedded) DSL	20	12%
Irregular data structures (e.g., quad-trees, oct-trees)	50	29%
Nested parallelism (e.g., map of map, map of fold, etc)	69	41%
Sparse data structures (e.g., sparse matrices)	64	38%
Support for graph processing	42	25%

• NESL

Which of the following frontend features would help you make better use of Accelerate or enable you to use Accelerate?



Accelerate as a standalone (non-embedded) DSL	20	12%
Irregular data structures (e.g., quad-trees, oct-trees)	50	29%
Nested parallelism (e.g., map of map, map of fold, etc)	69	41%
Sparse data structures (e.g., sparse matrices)	64	38%
Support for graph processing	42	25%

- NESL
- Data Parallel Haskell (DPH)

Nested Operations

Nested Structures

Nested Operations

MVM

Nested Structures

Nested Operations

MVM

fact n =
map (\m -> product [1..m]) [1..n]

Nested Structures

Nested Operations

MVM

```
fact n =
map (\m -> product [1..m]) [1..n]
```

Nested Structures

Vector (Vector e)

Nested Operations

MVM

```
fact n =
map (\m -> product [1..m]) [1..n]
```

Nested Structures

Vector (Vector e)

Array DIM2 (Vector e)

Nested Operations

MVM

```
fact n =
map (\m -> product [1..m]) [1..n]
```

Nested Structures

Vector (Vector e)

Array DIM2 (Vector e)

Trees



Stratification



Stratification



Stratification



Vectorisation (flattening)

• Vectorisation (flattening)

- First described by Blelloch and Sabot

- Vectorisation (flattening)
 - First described by Blelloch and Sabot

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Vectorisation (flattening)
 - First described by Blelloch and Sabot
 - Converts a nested parallel program into a flat parallel program

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Vectorisation (flattening)
 - First described by Blelloch and Sabot

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Converts a nested parallel program into a flat parallel program
- Programs must be pure, no side effects, no destructive updates, etc.

- Vectorisation (flattening)
 - First described by Blelloch and Sabot

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Converts a nested parallel program into a flat parallel program
- Programs must be pure, no side effects, no destructive updates, etc.
- Simple, but naive

- Vectorisation (flattening)
 - First described by Blelloch and Sabot

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Converts a nested parallel program into a flat parallel program
- Programs must be pure, no side effects, no destructive updates, etc.
- Simple, but naive
- Complexity problems

- Vectorisation (flattening)
 - First described by Blelloch and Sabot

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Converts a nested parallel program into a flat parallel program
- Programs must be pure, no side effects, no destructive updates, etc.
- Simple, but naive
- Complexity problems
- Focus of more recent work

- Vectorisation (flattening)
 - First described by Blelloch and Sabot
 - Converts a nested parallel program into a flat parallel program
 - Programs must be pure, no side effects, no destructive updates, etc.
 - Simple, but naive
 - Complexity problems
 - Focus of more recent work



Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Vectorisation (flattening)
 - First described by Blelloch and Sabot
 - Converts a nested parallel program into a flat parallel program
 - Programs must be pure, no side effects, no destructive updates, etc.
 - Simple, but naive
 - Complexity problems
 - Focus of more recent work



Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

- Vectorisation (flattening)
 - First described by Blelloch and Sabot
 - Converts a nested parallel program into a flat parallel program
 - Programs must be pure, no side effects, no destructive updates, etc.
 - Simple, but naive
 - Complexity problems
 - Focus of more recent work

Data Flo	w Fusion with Series	s Expression	s in Haskel
Ben Lippmeie	r [†] Manuel M. T. Chakravarty [†]	Gabriele Keller [†]	Amos Robinson [†]
	[†] Computer Science and University of New South V	<i>c c</i>	
	{benl,chak,keller,amosr}@		

Compiling Collection-Oriented Languages onto Massively Parallel Computers

GUY E. BLELLOCH

Carnegie Mellon University, School of Computer Science, Pittsburgh, Pennsylvania 15213-3890

AND

foo :: Int -> Float -> Float

 \mathcal{L}_n [foo] :: Vector Int -> Vector Float -> Vector Float

foo :: Int -> Float -> Float $\mathcal{L}_n[foo]$:: Vector Int -> Vector Float -> Vector Float The expression being transformed











 $\mathcal{L}_n[e1 \ e2] = \mathcal{L}_n[e1] \mathcal{L}_n[e2]$




bar :: Int -> Int bar = λx . $2^*x + 1$

bar :: Int -> Int bar = λx . $2^*x + 1$

 $\mathcal{L}_n[bar]$:: Vector Int -> Vector Int $\mathcal{L}_n[bar]$ = λx . (replicate (length x) 2) *[†] x +[†] (replicate (length x) 1)

bar :: Int -> Int bar = λx . 2*x + 1

 $\mathcal{L}_n[bar]$:: Vector Int -> Vector Int $\mathcal{L}_n[bar]$ = λx . (replicate (length x) 2) *[†] x +[†] (replicate (length x) 1)

What about vector functions?

bar :: Int -> Int bar = λx . 2*x + 1

 $\mathcal{L}_n[bar]$:: Vector Int -> Vector Int $\mathcal{L}_n[bar]$ = λx . (replicate (length x) 2) *[†] x +[†] (replicate (length x) 1)

What about vector functions?

sum :: Vector Int -> Int

bar :: Int -> Int bar = λx . 2*x + 1

 $\mathcal{L}_n[bar]$:: Vector Int -> Vector Int $\mathcal{L}_n[bar]$ = λx . (replicate (length x) 2) *[†] x +[†] (replicate (length x) 1)

What about vector functions?

sum :: Vector Int -> Int

 $\mathcal{L}_n[sum]$:: Vector (Vector Int) -> Vector Int

bar :: Int -> Int bar = λx . 2*x + 1

```
\mathcal{L}_n[bar] :: Vector Int -> Vector Int
\mathcal{L}_n[bar] = \lambda x. (replicate (length x) 2) *<sup>†</sup> x +<sup>†</sup> (replicate (length x) 1)
```

What about vector functions?

```
sum :: Vector Int -> Int

\mathcal{L}_n[sum] :: Vector (Vector Int) -> Vector Int

Nested vectors
```

• Vectors of pointers? Grossly inefficient.

- Vectors of pointers? Grossly inefficient.
- Blelloch's solution

- Vectors of pointers? Grossly inefficient.
- Blelloch's solution



- Vectors of pointers? Grossly inefficient.
- Blelloch's solution



• Will this solution work with multidimensional arrays?

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float \mathcal{L}_n [foo] :: Array sh Int -> Array sh Float -> Array sh Float

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float $\int_n [foo]$:: Array sh Int -> Array sh Float -> Array sh Float

• No, lifting to vectors is sufficient

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float $\int_n [foo]$:: Array sh Int -> Array sh Float -> Array sh Float

- No, lifting to vectors is sufficient
 - At the machine level it's all vectors anyway

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float $\int_n [foo]$:: Array sh Int -> Array sh Float -> Array sh Float

- No, lifting to vectors is sufficient
 - At the machine level it's all vectors anyway
- What about nested arrays?

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float \mathcal{L}_n [foo] :: Array sh Int -> Array sh Float -> Array sh Float

- No, lifting to vectors is sufficient
 - At the machine level it's all vectors anyway
- What about nested arrays?
 - But, we only need vectors of arrays

- Will this solution work with multidimensional arrays?
- Does it now require this?

foo :: Int -> Float -> Float \mathcal{L}_n [foo] :: Array sh Int -> Array sh Float -> Array sh Float

- No, lifting to vectors is sufficient
 - At the machine level it's all vectors anyway
- What about nested arrays?
 - But, we only need vectors of arrays

Vectors of arrays

type Vector' = ...a vector of arrays...

Vectors of arrays



Vectors of arrays



Nested Parallelism

Nested Operations	Nested Structures
MVM	Vector (Vector e)
	Array DIM2 (Vector e)
<pre>fact n = map (\m -> product [1m]) [1n]</pre>	Trees

Nested Parallelism

Nested Operations

MVM

```
fact n =
   map (\m -> product [1..m]) [1..n]
```

Nested Structures Vector (Vector e) Array DIM2 (Vector e) Trees

Nested Parallelism

Nested Operations

MVM

```
fact n =
   map (\m -> product [1..m]) [1..n]
```

Nested Structures Vector (Vector e) Array DIM2 (Vector e) Trees Sequences

• Sequences of arrays (or tuples of arrays)

- Sequences of arrays (or tuples of arrays)
- Can only be accessed linearly

- Sequences of arrays (or tuples of arrays)
- Can only be accessed linearly
- So map, fold and scan, but no permuting, indexing or constant time length

- Sequences of arrays (or tuples of arrays)
- Can only be accessed linearly
- So map, fold and scan, but no permuting, indexing or constant time length
- Like Haskell lists

- Sequences of arrays (or tuples of arrays)
- Can only be accessed linearly
- So map, fold and scan, but no permuting, indexing or constant time length
- Like Haskell lists
- Does that mean all the operations have to be made polymorphic over sequences and arrays?










mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

fromSeq :: Seq [Array sh e] -> Seq (Vector sh, Vector e)

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

fromSeq :: Seq [Array sh e] -> Seq (Vector sh, Vector e)

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

fromSeq :: Seq [Array sh e] -> Seq (Vector sh, Vector e)

Elements not always the same size

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

collect :: Arrays a => Seq a -> Acc a

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]

collect :: Arrays a => Seq a -> Acc a

mapSeq :: (Acc a -> Acc b) -> Seq [a] -> Seq [b]

toSeq :: Acc (Array (sh:.Int) e) -> Seq [Array sh e]



mvm mat vec =

mvm mat vec =

\$ toSeq mat

mvm mat vec =

- \$ mapSeq (dotp vec)
- \$ toSeq mat

mvm mat vec =

- \$ fromSeq
- \$ mapSeq (dotp vec)
- \$ toSeq mat

mvm mat vec = snd

- \$ collect
- \$ fromSeq
- \$ mapSeq (dotp vec)
- \$ toSeq mat

- Sequentially
 - The processing of each element has to expose enough parallelism

- Sequentially
 - The processing of each element has to expose enough parallelism
- As one large vector
 - Use the lifting transform
 - Space problems

- Sequentially
 - The processing of each element has to expose enough parallelism
- As one large vector
 - Use the lifting transform
 - Space problems
- Chunk-wise
 - Work on many elements in parallel















Ideal foldSeq :: (Acc a -> Acc a -> Acc a)
 -> Acc a
 -> Seq [a]
 -> Seq (a)

```
 Ideal foldSeq :: (Acc a -> Acc a -> Acc a)
 -> Acc a
 -> Seq [a]
 -> Seq (a)
```

• Basic

```
foldSeq :: (Exp a -> Exp a -> Exp a)
-> Exp a
-> Seq [Scalar a]
-> Seq (Scalar a)
```

```
 Ideal foldSeq :: (Acc a -> Acc a -> Acc a)
 -> Acc a
 -> Seq [a]
 -> Seq (a)
```

• Basic

```
foldSeq :: (Exp a -> Exp a -> Exp a)
-> Exp a
-> Seq [Scalar a]
-> Seq (Scalar a)
```

- Ideal foldSeq :: (Acc a -> Acc a -> Acc a)
 -> Acc a
 -> Seq [a]
 -> Seq (a)
- Basic

foldSeq :: (Exp a -> Exp a -> Exp a)
 -> Exp a
 -> Seq [Scalar a]
 -> Seq (Scalar a)



• Basic





Basic



Better

foldSeqFlatten :: (Acc a -> Acc (Vector sh) -> Acc (Vector b) -> Acc a
 -> Acc a
 -> Seq [Array sh b]
 -> Seq a







• What's the best size?

- What's the best size?
- A lot of factors involved

- What's the best size?
- A lot of factors involved
 - Number of GPU cores

- What's the best size?
- A lot of factors involved
 - Number of GPU cores
 - Available device Memory

- What's the best size?
- A lot of factors involved
 - Number of GPU cores
 - Available device Memory
 - The computation itself

- What's the best size?
- A lot of factors involved
 - Number of GPU cores
 - Available device Memory
 - The computation itself
 - Space and time analysis of array computations

- What's the best size?
- A lot of factors involved
 - Number of GPU cores
 - Available device Memory
 - The computation itself
 - Space and time analysis of array computations
- Still ongoing work

Streaming

- Sequences allow for working with data sets larger than available GPU memory
 - A painful experience before
- Streaming operations
- streamIn :: Arrays a => [a] -> Seq [a]
- streamOut :: Arrays a => Seq [a] -> [a]

Lots more to do

- Regularity
 - Sequences where all elements are the same size
- Streaming from different sources
- Stateful operations
 - Scans
- Nested sequences

Questions?