TDDD56 Multicore Computing /
TDDC78 Programming of Parallel Computers

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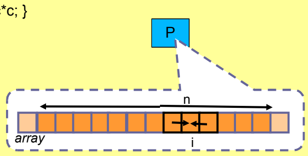
Parallelization Patterns and Algorithmic Skeletons

An Introduction

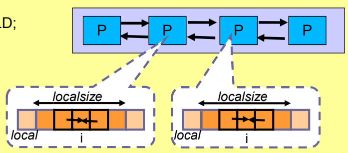
Example 1: 1D smoothening filter in C

```
…
float filter (float a, b, c) { return wa*a + wb*b + wc*c; }
…
void main ( int argc, char *argv[] )
{
  float *array = new_FloatArray( n+2 );
  float *tmp = new_FloatArray( n+2 );
  …
  while ( globalerr > 0.1 ) {
     for (i=1; i<=n; i++)
        tmp[i] = filter( array[i-1], array[i], array[i+1] );
     globalerr = 0.0;
     for (i=1; i<=n; i++)
        globalerr = fmax (globalerr, fabs(array[i] – tmp[i]) );
     for (i=1; i<=n; i++)
        array[i] = tmp[i];
  }
}
```

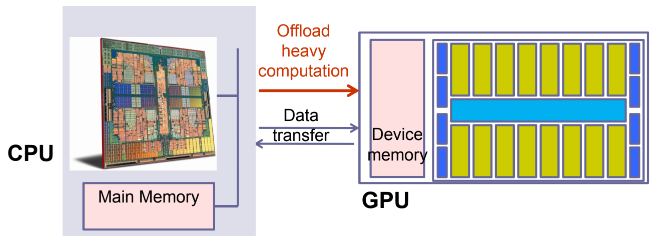


Example 1: 1D smoothening filter in C + MPI

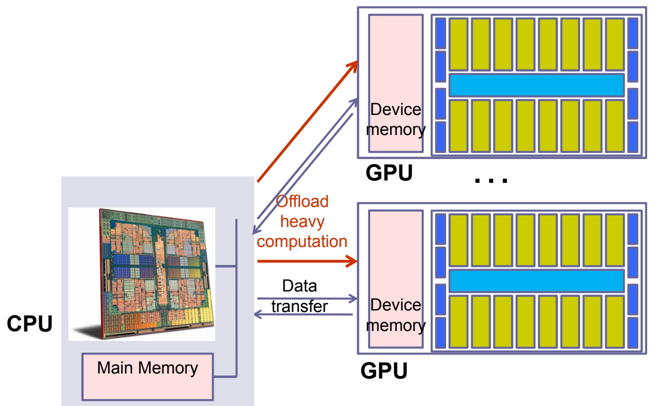
```
…
void main ( int argc, char *argv[] ) {
   MPI_Comm com = MPI_COMM_WORLD;
   MPI_Init ( &argc, &argv );
   MPI_Comm_size ( com, &np );
   MPI_Comm_rank ( com, &me );
   …
   localsize = (int) ceil ( (float) n / np );
   local = new_FloatArray( localsize + 2);
   …
   while ( globalerr > 0.1 ) {
      if (me>0)       MPI_Send ( local+1,  1, MPI_FLOAT,  left_neighbor, 10,  com );
      if (me<np-1)  MPI_Send ( last, 1, MPI_FLOAT,  right_neighbor,  20,  com );
      for (i=1; i<=localsize; i++)
         tmp[i] = filter( local[i-1], local[i], local[i+1] );
      if (me<np-1)  MPI_Recv ( tmp,  1,  MPI_FLOAT,  right_neighbor,  10,  com,  … );
      if (me>0)       MPI_Recv ( tmp+localsize+1, 1, MPI_FLOAT,  left_neighbor,  20,  com,  … );
      tmp[1] = filter( local[0], local[1], local[2] );
      tmp[localsize] = filter( local[localsize-1], local[localsize], local[localsize+1] );
      localerr = 0.0;
      for (i=1; i<=localsize; i++)  localerr = fmax( localerr, fabs ( local[i]-tmp[i] ));
      MPI_Allreduce ( &localerr, &globalerr,  1,  MPI_FLOAT,  MPI_MAX,  com );
      for (i=1; i<localsize; i++)
         local[i] = tmp[i];
 }  …
```



Example 2: GPU-Based Systems

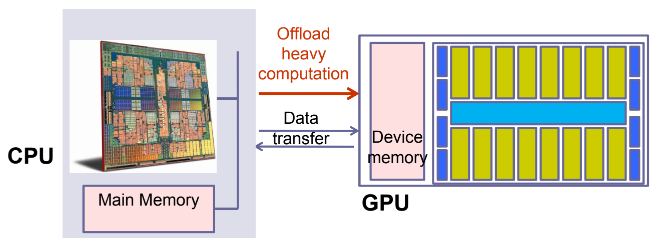


Example 2: GPU-Based Systems



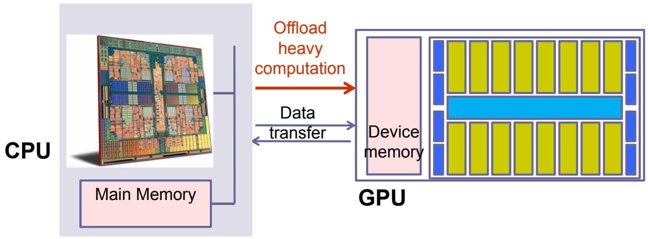
Example 2 Programming of GPU-Based Systems …

- Portability ?
- Programmability ?
- Performance portability ?



Example 2:
Programming of GPU-based Systems … with OpenCL™

- **Portability** ☺
- **Programmability** ☹ (low level)
- **Performance portability** ☹ (requires reoptimization)



Complexity of *Parallel* Algorithms and Programs

- Many different parallel programming models
  - Identify parallelism (”tasks”)
  - Synchronization and communication?
  - Memory structure, -consistency model?
  - Resource allocation, mapping, scheduling?
  - Using accelerators, e.g. GPU? Or several GPUs?
- Error prone, hard to debug
- Code portability?
- Performance portability??

Can we make parallel programming as easy as sequential programming?

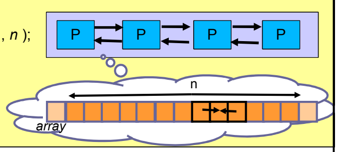
Observation

- Same characteristic form of parallelism, communication, synchronization re-applicable for all occurrences of the same specific **structure** of computation
  ((parallel) algorithmic paradigm, building block, pattern, …)
  - Elementwise operations on arrays
  - Reductions
  - Scan (Prefix-op)
  - Divide-and-Conquer
  - Farming independent tasks
  - Pipelining
  - …
- Most of these have both sequential and parallel implem.'s
- Idea: Reusable (customizable) generic constructs (*skeletons*)

Example 1, cont.:
1D smoothening in C + Skeletons

```
…
float filter (float a, b, c) { return wa*a + wb*b + wc*c; }

float elemError ( float a, b ) { return fabs ( a – b ); }
...
void main ( int argc, char *argv[] ) {
   …
   DistrFloatArray *array = new_DistrFloatArray ( n + 2 );
   DistrFloatArray *tmp = new_DistrFloatArray ( n + 2 );
   DistrFloatArray *err = new_DistrFloatArray ( n + 2 );
   ...
   while ( globalerr > 0.1 )  {
       map_with_overlap( filter, 1, tmp, array+1, n );
       map( elemError, err, array+1, tmp, n );
       reduce( fmax, &globalerr, err, n );
       map( copy, array+1, tmp, n );
   }
   ...
}
```



Data parallelism

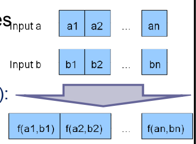
Given:

- One or several data containers x with n elements, e.g. array(s) $x = (x_1,...x_n)$, $z = (z_1,…,z_n)$, …
- An operation f on individual elements of $x, z, …$ (e.g. *incr, sqrt, mult*, ...)

Compute: $y = f(x) = (f(x_1), ..., f(x_n))$

Parallelizability: Each data element defines a task

- Fine grained parallelism
- Portionable, fits very well on all parallel architectures



Notation with higher-order function*:*

- $y =$ ***map*** (f, x)

Variant: map with overlap: $y_i = f\,(x_{i-k}, …, x_{i+k})$, $i = 0,…,n-1$ for some small constant k

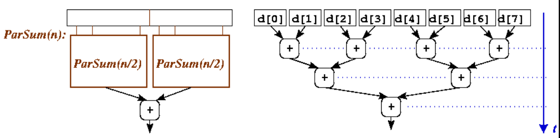
Data-parallel Reduction

Given:

- A data container x with n elements, e.g. array $x = (x_1,...x_n)$
- A <u>binary, associative</u> operation *op* on individual elements of x (e.g. *add, max, bitwise-or*, ...)

Compute: $y = OP_{i=1…n}\, x = x_1 \text{ op } x_2 \text{ op } ... \text{ op } x_n$

Parallelizability: Exploit associativity of op



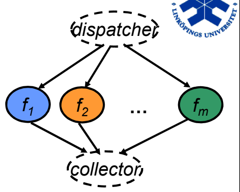
Notation with higher-order function*:*

- $y =$ ***reduce*** (op, x)

Task farming

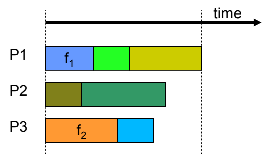
Independent computations $f_1, f_2, ..., f_m$
could be done in parallel and/or in arbitrary order, e.g.

- independent loop iterations
- independent function calls



Scheduling problem

- n tasks onto p processors
- static or dynamic
- Load balancing



Notation with higher-order function:

- $(y_1,...,y_m)$ = ***farm*** $(f_1, ..., f_m)$ $(x_1,...,x_n)$

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Parallel Divide-and-Conquer

(Sequential) Divide-and-conquer:

- *Divide*: Decompose problem instance P in one or several <u>smaller independent</u> instances of the same problem, $P_1, ..., P_k$
- For all i: If P_i *trivial*, solve it *directly*.
- Else, solve P_i by recursion.
- *Combine* the solutions of the P_i into an overall solution for P

Parallel Divide-and-Conquer:

- Recursive calls can be done in parallel.
- Parallelize, if possible, also the divide and combine phase.
- Switch to sequential divide-and-conquer when enough parallel tasks have been created.

Notation with higher-order function:

- *solution* = ***DC*** (*divide, combine, istrivial, solvedirectly, n, P*)

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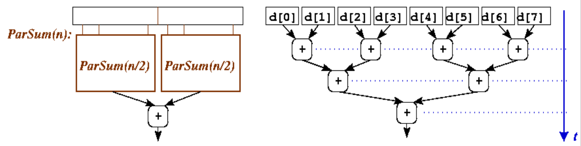
Example: Parallel Divide-and-Conquer



Example: **Parallel Sum** over integer-array x

Exploit associativity:

$Sum(x_1,...,x_n)$ = $Sum(x_1,...x_{n/2}) + Sum(x_{n/2+1},...,x_n)$

Divide: trivial, split array x in place

Combine is just an addition.

y = ***DC*** (*split, add, nIsSmall, addFewInSeq, n, x*)

Data parallel reductions are an important special case of DC.

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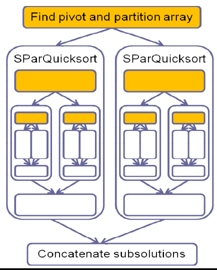
Example: Parallel Divide-and-Conquer (2)

Example: **Parallel QuickSort** over a float-array x

Divide: Partition the array (elements <= pivot, elements > pivot)

Combine: trivial, concatenate sorted sub-arrays

sorted = ***DC*** (*partition, concatenate, nIsSmall, qsort, n, x*)



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Skeletons

Skeletons are reusable, parameterizable components with well defined semantics for which efficient parallel implementations may be available.

Inspired by <u>higher-order functions</u> in functional programming

One or very few skeletons per parallel algorithmic paradigm

- map, farm, DC, reduce, pipe, scan ...

<u>Parameterised</u> in user code

- Customization e.g. by instantiating a skeleton template in a user function

Composition of skeleton instances in program code
normally by <u>sequencing+data flow</u>

- e.g. *squaresum(x)* can be defined by

```
{
    tmp = map( sqr, x );
    return reduce( add, tmp );
}
```

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Pipelining

applies a sequence of <u>dependent</u> computations $(f_1, f_2, ..., f_k)$ elementwise to data sequence $x = (x_1,...,x_n)$

- For fixed x_j, compute $f_i(x_j)$ before $f_{i+1}(x_j)$
- Computations of f_i on <u>different</u> x_j are independent.

Parallelizability: Overlap execution of all f_i for k subsequent x_j

- *time=1: compute* $f_1(x_1)$
- *time=2: compute* $f_1(x_2)$ *and* $f_2(x_1)$
- *time=3: compute* $f_1(x_3)$ *and* $f_2(x_2)$ *and* $f_3(x_1)$
- *...*
- Total time: $O((n+k) \max_i(time(f_i)))$ with k processors

Notation with higher-order function:

- $(y_1,...,y_n)$ = ***pipe*** $((f_1, ..., f_k), (x_1,...,x_n))$

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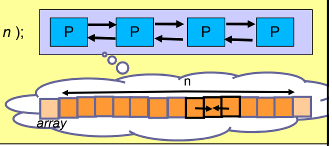
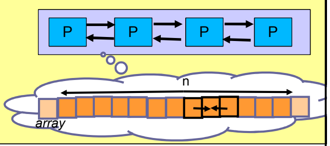
Example 1 revisited: 1D smoothening in C + Skeletons

```
…
float filter (float a, b, c) { return wa*a + wb*b + wc*c; }

float elemError ( float a, b ) { return fabs ( a – b ); }
…
void main ( int argc, char *argv[] ) {
   …
   DistrFloatArray *array = new_DistrFloatArray ( n + 2 );
   DistrFloatArray *tmp = new_DistrFloatArray ( n + 2 );
   DistrFloatArray *err = new_DistrFloatArray ( n + 2 );
   …
   while ( globalerr > 0.1 ) {
       map_with_overlap( filter, 1, tmp, array+1, n );
       map( elemError, err, array+1, tmp, n );
       reduce( fmax, &globalerr, err, n );
       map( copy, array+1, tmp, n );
   }
   …
}
```



Example 1 revisited: 1D smoothening in C++ + Skeletons

```
…
float filter (float a, b, c) { return wa*a + wb*b + wc*c; }

float elemError ( float a, b ) { return fabs ( a – b ); }
…
void main ( int argc, char *argv[] ) {
   …
   Vector<float> array = new Vector<float> ( n + 2 );
   Vector<float> tmp = new Vector<float> ( n + 2 );
   Vector<float> err = new Vector<float> ( n + 2 );
   …
   while ( globalerr > 0.1 ) {
       map_with_overlap( filter, 1, tmp, array );
       map( elemError, err, array, tmp );
       reduce( fmax, &globalerr, err );
       map( copy, array, tmp );
   }
   …
}
```



Generic containers (e.g., Vector<>)
provide a cleaner interface and encapsulate metadata (e.g., size) and internal state of operand data (e.g., storage format and location, distribution, modified, …)

Skeletons (cont.)

Skeletons <u>encapsulate</u> completely all coordination of parallelism and platform-specific issues

Threads/Process creation/termination, communication, synchronization

→ Code portability

→ Reuse of the coordination code across multiple skeleton instances

Skeletons may also have a <u>sequential</u> implementation

Uniform treatment of sequential and parallel programming

Skeleton Programming Systems

4 basic approaches for realizing skeletons (esp., parameterisation mechanism):

- Library of higher-order functions (functional or imperative)
- OO class library *(subclass and define abstract parameter method(s))*
- New language constructs (*intrinsics / compiler-known functions*)
- Generative programming, Static metaprogramming (Macros / *templates*)

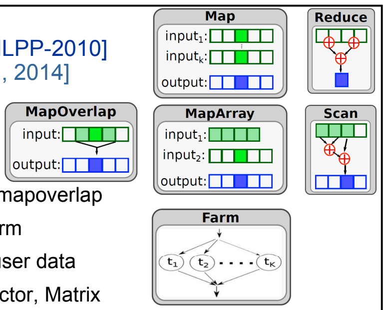
Many research prototypes, e.g.:

- *P3L* - C + skeletons
- *SCL, Eden, HDC* - functional
- *eSkel* - C + MPI
- *Lithium* - Java + RMI
- *BlockLib* - C + macros (generative) + DMA for Cell BE
- *muskel, ASSIST* - C++, grid computing
- *MueSLi, QUAFF* - C++ based, MPI
- *SkePU*, SkelCL - C++ based, for GPU based systems

Domain-specific Skeleton Systems, e.g.

- *MallBa* (combinatorial optimization: BB, DP, GA, …)
- *MapReduce* (distributed data mining, Google)

SkePU [Enmyren, K. HLPP-2010] [Dastgeer 2011, 2014]



- C++ template library
- 6 dataparallel skeletons
  - Map, reduce, scan, mapreduce, maparray, mapoverlap
- 1 task-parallel skeleton: farm
- STL-based containers for user data
  - Smart containers for Vector, Matrix
- Generation of platform-specific variants for user functions
- Multiple back-ends: C, OpenMP, OpenCL, CUDA, StarPU
  - Hybrid CPU-GPU execution (with StarPU backend)
- Multi-GPU support
- Low overhead
- Tunable

The SkePU Multi-Backend Skeleton Library

Example: Dot Product

```
#include <iostream>

#include "skepu/vector.h"
#include "skepu/mapreduce.h"

BINARY_FUNC(plus, double, a, b,
   return a+b;
)

BINARY_FUNC(mult, double, a, b,
   return a*b;
)

….
```

```
….

int main()
{
   skepu::MapReduce<mult, plus>
         dotProduct(new mult, new plus);

   skepu::Vector<double> v0(1000,2);
   skepu::Vector<double> v1(1000,2);

   double r = dotProduct(v0,v1);

   std::cout<<"Result: " <<r <<"\n";

   return 0;
}
```

Generate a skeleton instance (function dotProduct)

Generic container holds operand data

Macro expands to platform-specific code versions for user functions

Invocation at run time

SkePU: Generating platform-specific variants of user functions

```
BINARY_FUNC(plus, double, a, b,
    return a+b;
)
```

expands to

Macro expands to a struct with platform-specific versions of the user function

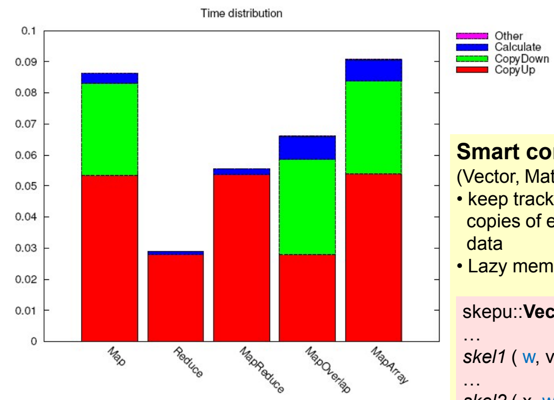
```
struct plus
{
    skepu::FuncType funcType;
    std::string func_CL;
    std::string funcName_CL;
    std::string datatype_CL;
    plus()
    {
        funcType = skepu::BINARY;
        funcName_CL.append("plus");
        datatype_CL.append("double");
        func_CL.append(
        "double plus(double a, double b)\n"
        "{\n"
        "    return a+b;\n"
        "}\n");
    }
    double CPU(double a, double b)
    {
        return a+b;
    }
    __device__ double CU(double a, double b)
    {
        return a+b;
    }
};
```

OpenCL

CPU

CUDA

Importance of Data Transfer Optimization



Smart containers (Vector, Matrix):
- keep track of current copies of element data
- Lazy memory copying

skepu::**Vector** v, w, x;
…
skel1 (w, v);
…
skel2 (x, w);

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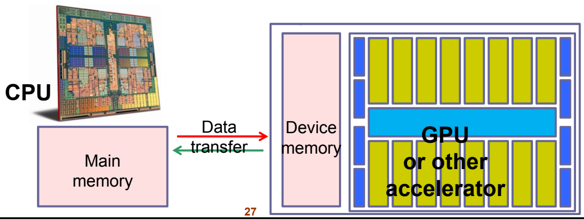
SkePU Containers

- For non-scalar operand data
  - STL-like Vector
  - Matrix
- Handle transparent data access and memory transfers between host and device ("***smart containers***") [Dastgeer, K. 2015]
  - Lazy memory copying
  - Implements (coarse-grained) memory coherence in software



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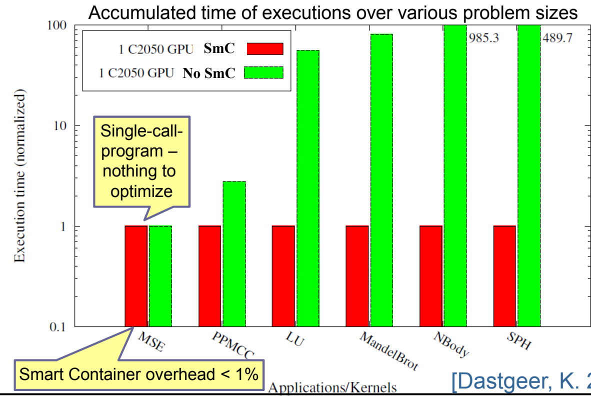
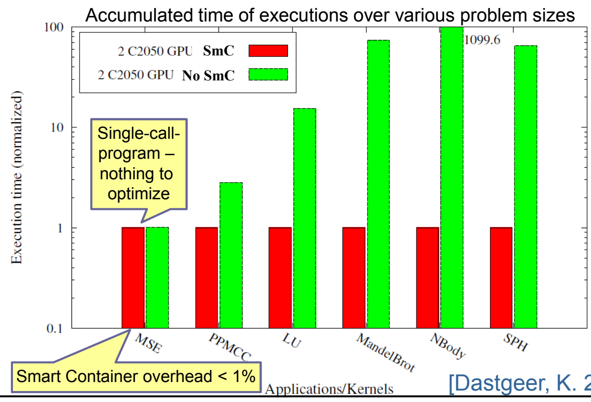
Evaluation
Speedup by (new) Smart Containers – 1 GPU



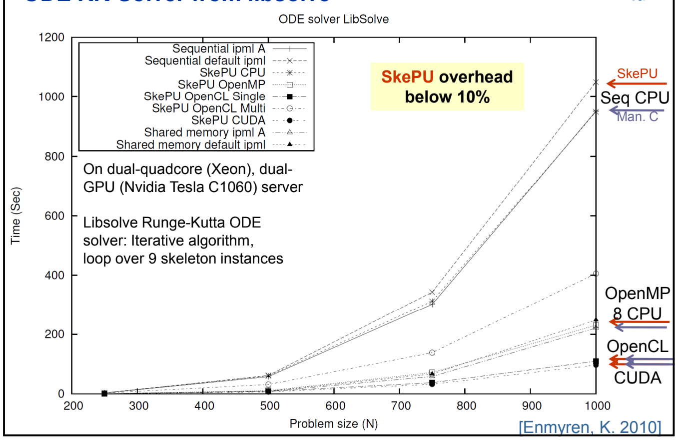
[Dastgeer, K. 2015]

Evaluation
Speedup by (new) Smart Containers – 2 GPUs



[Dastgeer, K. 2015]

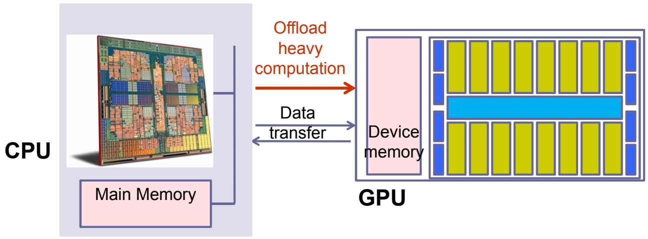
Comparison: SkePU vs hand-written code
ODE RK-Solver from libsolve



[Enmyren, K. 2010]

Programming of GPU-based Systems … with SkePU, so far…

- Portability ☺
- Programmability ☺
- Performance portability ☹

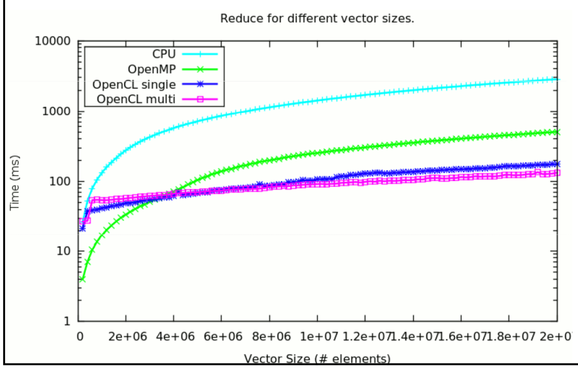


Implementation selection

- For each skeleton call, we need to decide:
  - Which skeleton implementation to use
- The decision depends upon:
  - Skeleton type
  - User function / actual computation
  - Target architecture
  - Problem size
  - etc.

SkePU Tunability [Dastgeer *et al.* IWMSE-2011]

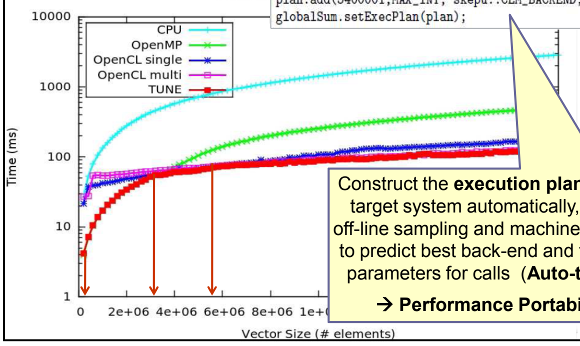
- Different Back-Ends, each with tunable parameters



SkePU Tunability [Dastgeer *et al.* IWMSE-2011]

- Execution plan

```
skepu::Reduce<plus> globalSum(new plus);
skepu::ExecPlan plan;
plan.add(1,3500, skepu::CPU_BACKEND);
plan.add(3501,3200000, skepu::OMP_BACKEND, 8);
plan.add(3200001,5400000, skepu::CL_BACKEND, 65536, 128);
plan.add(5400001,MAX_INT, skepu::CLM_BACKEND, 65536, 128);
globalSum.setExecPlan(plan);
```



Construct the **execution plan** for the target system automatically, using off-line sampling and machine learning to predict best back-end and tunable parameters for calls (**Auto-tuning**)

→ Performance Portability

Auto-Tuning SkePU

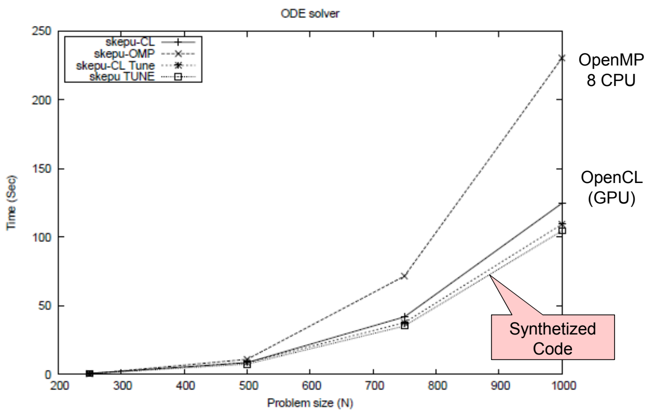
- Use off-line, machine learning approach to predict best back-end and its tunable parameters for given problem size
- Basic tunable parameters for each skeleton:
  #threads (on CPU), thread block size + grid size (on GPU)

```
1 --- 50000 OMP_BACKEND 8
50001 --- 150000 CL_BACKEND 32 16384
150001 --- 225000 CL_BACKEND 128 2048
225001 --- 1050000 CL_BACKEND 512 2048
...
71500001 --- INFINITY CLM_BACKEND 256 2048
```

Execution plan

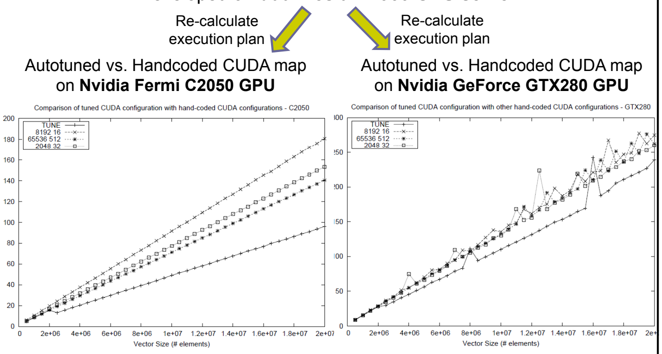
- Performance portability demonstrated across multiple GPU systems [Dastgeer, K. IWMSE'11, APPT'13]

RK-ODE-solver, synthetized from tuned SkePU skeletons



Performance portability demonstrated with autotuned SkePU skeletons

Developed on **dual-Tesla C1060 GPU server**



→ **Source code left untouched when migrating to new system!**

Alternative: Construct execution plan implicitly at runtime (StarPU back-end)

Coulombic application, 24K x 24K matrix, 3 successive executions, 1 CPU + 1 GPU.
First iteration: No data on GPU, no performance history → greedy partitioning
Data-aware scheduling (StarPU) learns at runtime
Later iterations: Some data on GPU, more performance-aware decisions: 7x speedup

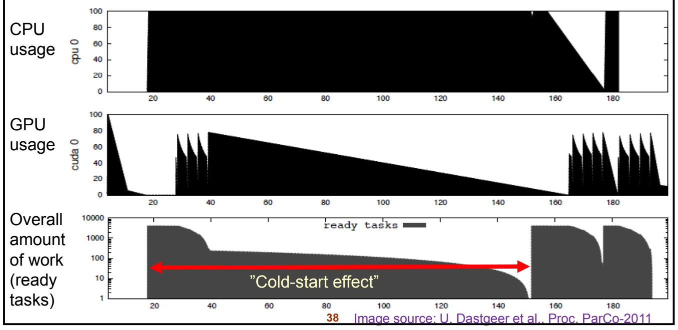
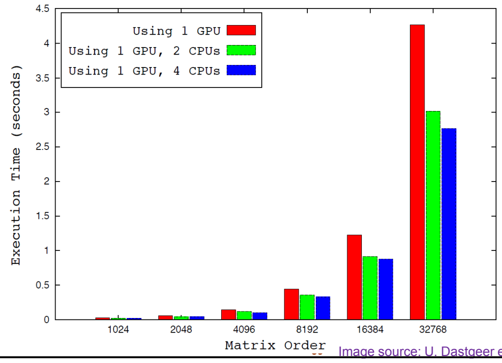


 Image source: U. Dastgeer et al., Proc. ParCo-2011

SkePU backend for StarPU runtime system

- Hybrid execution of tasks created from a single skeleton instance



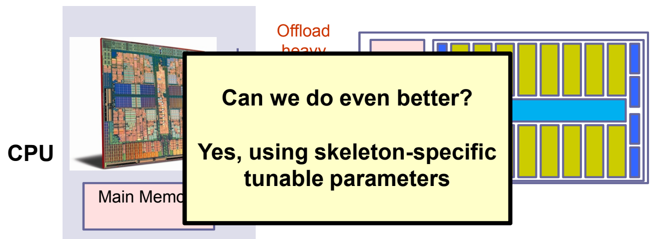
Coulombic Potential grid benchmark for different matrix sizes.

Platform: Dual-quadcore Xeon with Nvidia C2050 GPUs

Image source: U. Dastgeer et al., Proc. ParCo-2011

Programming of Heterogeneous Multi-/Manycore Systems … with SkePU

- Portability ☺
- Programmability ☺
- Performance portability ☺

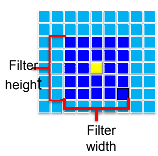


Can we do even better?

Yes, using skeleton-specific tunable parameters

Example: Autotunable 2D MapOverlap Skeleton

- Generic 2D MapOverlap skeleton
  - 2D Stencil computations
  - CUDA and OpenCL implementations for GPUs
    - Performance optimizations:
      - Use constant memory, shared memory, tiling



- Performance Portability →
  - Best tiling factor depends on architecture + user function
  - Parametric auto-tuning → predictor at runtime for best tiling factor
- Details: [Dastgeer, K., MULTIPROG-2012]

Example: Autotunable 2D MapOverlap Skeleton

GPU architecture	Memory-optimized	Adaptive Tiling, using Φ_{tiling}	Speedup
C2050	76 GFLOP/s	274 GFLOP/s	**3.6x**
GTX280	41 GFLOP/s	95 GFLOP/s	**2.3x**
8800GT	25 GFLOP/s	59 GFLOP/s	**2.4x**

Baseline:
with standard optimizations
(e.g. usage of shared and constant memory).

Conclusion (SkePU)

- SkePU skeletons are pre-defined generic components
  - For frequently occurring algorithmic patterns
  - map, reduce, scan, mapoverlap, farm …
- Multiple back-ends, multi-GPU support
  - Seq, OpenMP, OpenCL, CUDA
  - StarPU backend for task parallelism and hybrid parallel execution
  - MPI back-end for GPU clusters
- Smart containers to avoid unnecessary data transfers
- Auto-tunable
  - Off-line + on-line tuning of resource allocation for calls
  - Parametric autotuning for specific skeletons

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Other Skeleton Programming Frameworks

Example: Intel TBB Algorithm Templates

Intel Threading Building Blocks (TBB)

- Library for programming multicore processors
- extends C++ with a task based parallel programming model including
  - tasks (also fine-grained), no threads
  - high-level parallel *algorithm templates* (functions - nestable),
    - data-parallel (e.g. parallel for, reduce, scan) and task-parallel (e.g. pipe)
    - User functions (body) more coarse-grained than individual elements, to better perform on CPU
  - concurrent containers,
  - mutexes, atomic operations, etc.
- sophisticated run-time task scheduling mechanism,
  - At runtime, the TBB run-time system creates tasks and assigns them to threads which the OS schedules to cores
  - Dynamic load balancing by *task stealing*.

TBB example

Intel: TBB tutorial, 2010, www.intel.com and threadingbuildingblocks.org

- Data-parallel loop in TBB

```
#include "tbb/tbb.h”
void ParallelSquare( float a[], size_t n )
{
   parallel_for( blocked_range<size_t>(0,n),
                 Square(a));
}
```

- Class Square defines a **functor** (= function object, instance of a class containing a member function that overloads the (.) operator → invoking ”()” looks like a function call)
  - ”element function”, ”user function”:
    Works on a contiguous subarray (index subrange) at a time

Summary

- **Skeleton programming**
  - Algorithmic paradigms
  - Predefined generic parallel components, parameterized in user code
  - Hiding complexity (parallelism and low-level programming)
  - ☺ Abstraction
  - 😐 Enforces structuring
  - ☺ Parallelization for free
  - ☺ Easier to analyze and transform
  - ☹ Requires complete understanding and rewriting
  - ☹ Available skeleton set does not always fit
  - ☹ May lose some efficiency compared to manual parallelization
- Industry (beyond HPC domain) has adopted skeletons
  - map, reduce, scan in many modern parallel programming APIs
    - e.g., Intel Threading Building Blocks (TBB): par. for, par. reduce, pipe
    - NVIDIA Thrust
  - Google MapReduce (for distributed data mining applications)

Thesis projects available!

- Extension of SkePU
  - New skeletons, new containers, new platforms…
- Porting applications to SkePU
  - Medical image visualization
  - Linear equation system solvers
  - Deep learning / Convolutional neural networks
  - Image processing …
- Improvements of the autotuning framework
  - Statistical techniques for performance modeling
- Cooptimized selection for multiple calls to consider inter-call effects
- SkePU is an open-source project
  - Documentation + download: www.ida.liu.se/~chrke/skepu

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Questions?

Some literature on skeleton programming

M. Cole: *Algorithmic Skeletons: Structured Management of Parallel Computation*, MIT Press & Pitman, 1989. http://homepages.inf.ed.ac.uk/mic/Pubs/pubs.html

S. Pelagatti: *Structured Development of Parallel Programs.* Taylor and Francis, 1998.

F. Rabhi and S. Gorlatch (eds.): *Patterns and Skeletons for Parallel and Distributed Computing*. Springer-Verlag, 2003.

M. Ålind, M. Eriksson, C. Kessler: BlockLib: A Skeleton Library for Cell Broadband Engine. Proc. ACM Int. Worksh. on Multicore Software Engineering, Leipzig, 2008.

J. Enmyren, C. Kessler: SkePU: A Multi-Backend Skeleton Programming Library for Multi-GPU Systems. Proc. HLPP-2010 Int. Workshop on High-Level Parallel Programming, Sep. 2010, Baltimore, USA. ACM.

U. Dastgeer: Performance-Aware Component Composition for GPU-Based Systems. PhD thesis, Linköping University, 2014. Chapter 3.

U. Dastgeer, C. Kessler: Smart Containers and Skeleton Programming for GPU-based Systems. *Int. J. of Parallel Programming*, Springer, March 2015.

SkePU Documentation and Download: http://www.ida.liu.se/~chrke/skepu

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Glossary

- **Performance Portability**

  … is the ability of a program to automatically adapt to a new execution platform to achieve an automated best-effort optimization of performance on the new target system, without manual rewriting / reoptimization.

- **[Algorithmic] Skeleton**

  … is a pre-defined, generic software construct for high-level programming
  that implements a specific *pattern* of control and data flow,
  that can be *parameterized* by problem-specific code to instantiate a problem-specific function, and
  whose implementation internally *encapsulates* all platform-specific details such as parallelism, heterogeneity, communication and synchronization.

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