An Overview of FastFlow: Combining Pattern-Level Abstraction and Efficiency in GPGPUs

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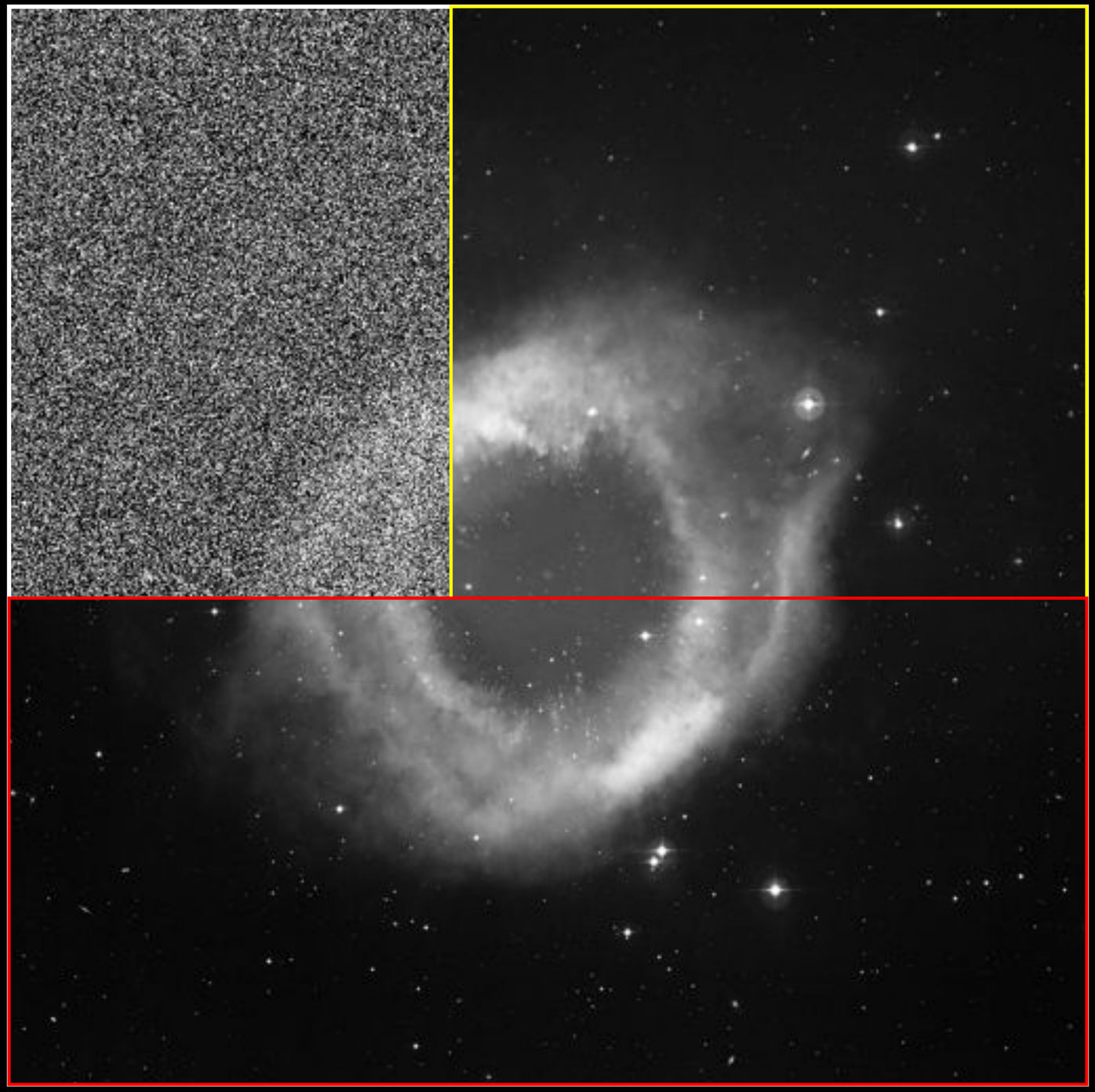
Outline

- Motivational example
  - An effective (and quite universal) image/video denoiser
  - Paradigmatic programming pattern for GPGPUs?
- On patterns for multicore and GPGPUs
  - FastFlow
  - Some performance results
  - A demo

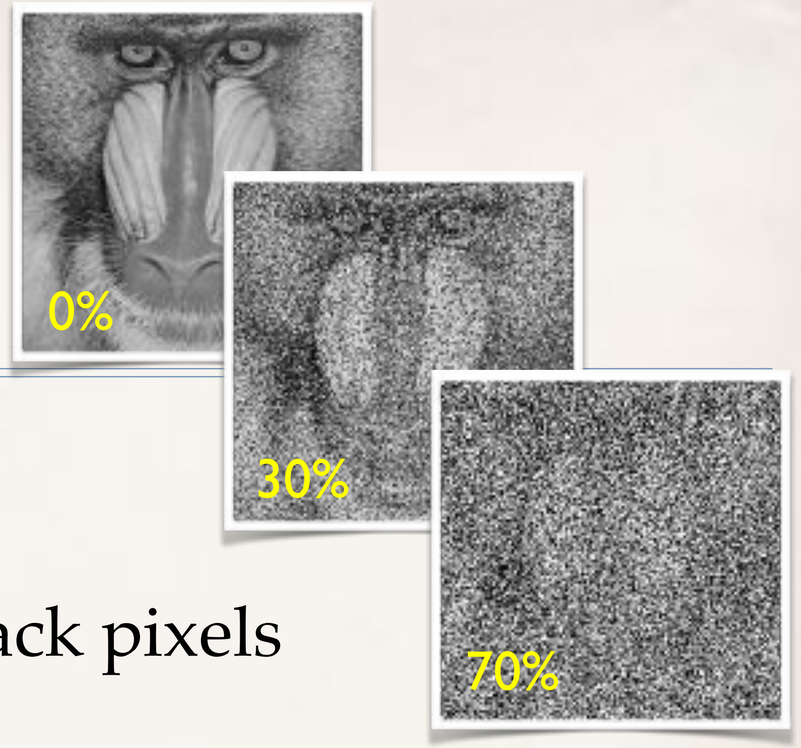
Salt&Pepper
noise 70%



Restored

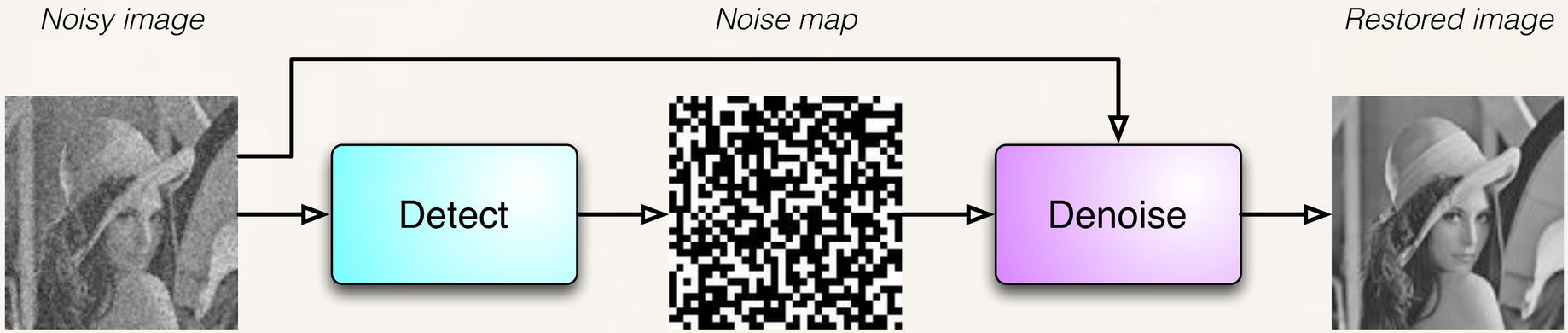
Original

Salt & Pepper and Gaussian noises



- Electronic and signal noise
- S&P Uniform distribution of “saturated” white/black pixels
  - Measured as percentage of affected vs overall pixels
- Gaussian: White additive noise in the frequency domain
  - Affect all pixels, with an additive “white” value distributed as a Gaussian
- Typically restored using statistic filters: e.g. median, median-adaptive
- Not satisfactory for high levels of noise

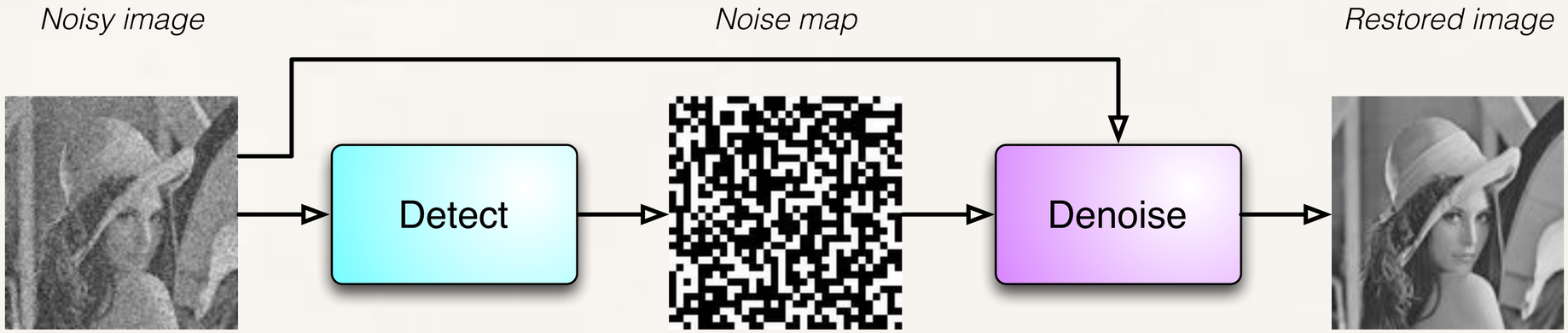
Two-stage restoring



- progressive-switching/adaptive median
- neural/bayesian networks, fuzzy, …
- variational
- statistic

- Decouple detection decoupled from restoration
  - Pixels considered not outliers are not altered by restoration
  - False positives impair restoration quality

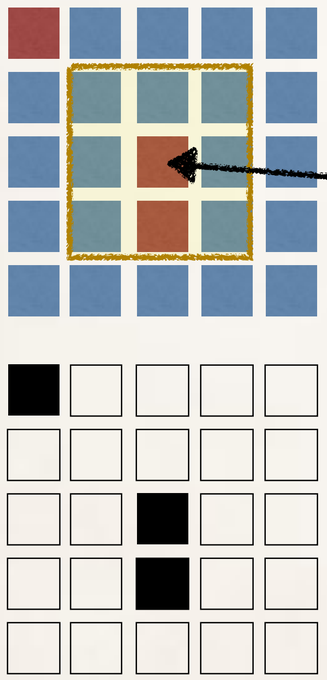
Two-stage restoring



- **progressive-switching/adaptive median**
- neural/bayesian networks, fuzzy, …
- **variational**
- statistic

- Statistic detection + variational restoration
  - High quality, edge-preserving filtering
  - Much more computational demanding, not really viable without parallelism
    - Matlab on 256x256 image with 50% of noise requires dozen of minutes
  - Stages can be pipelined

Variational De-noising: an iterative optimisation problem

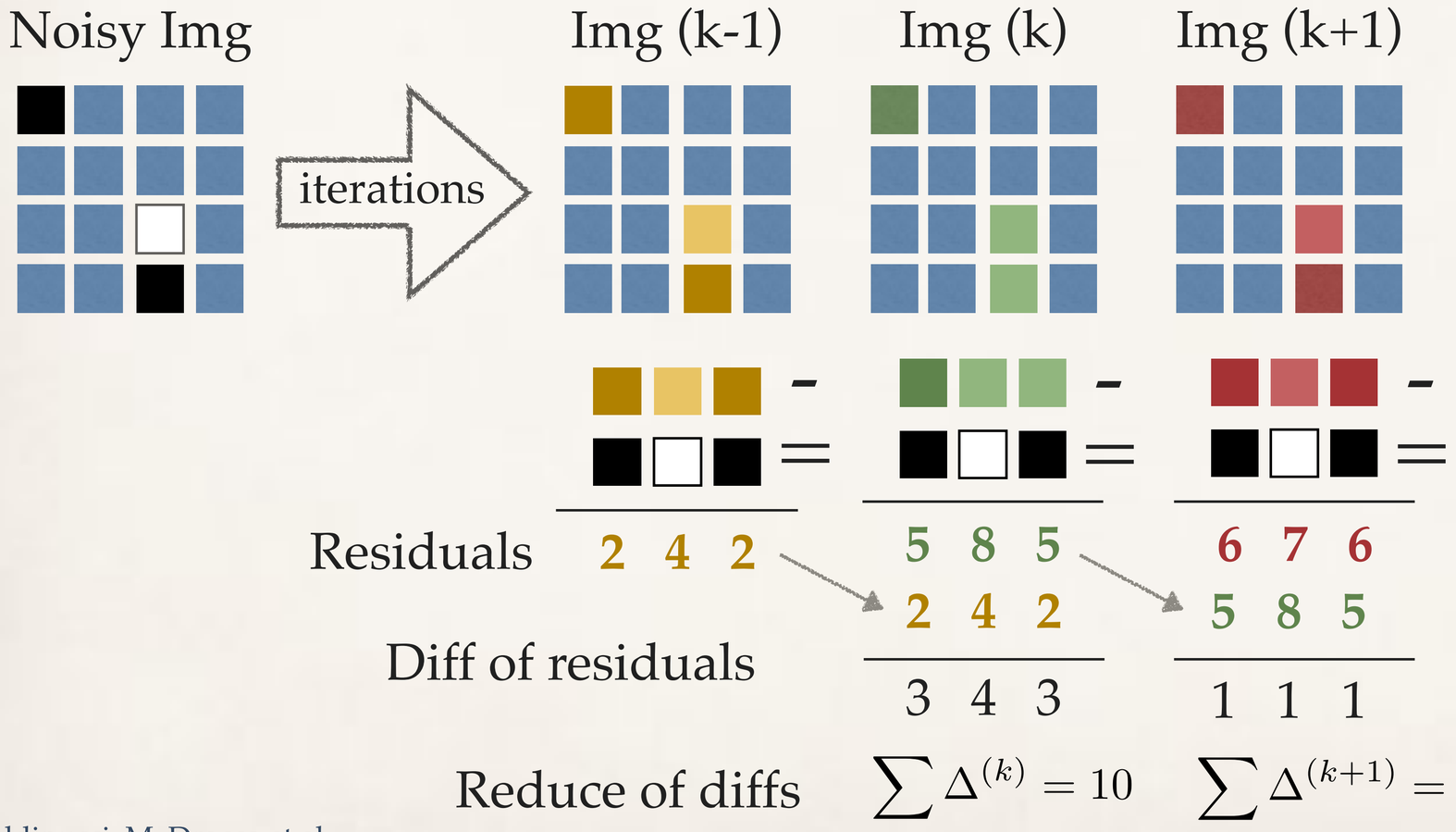


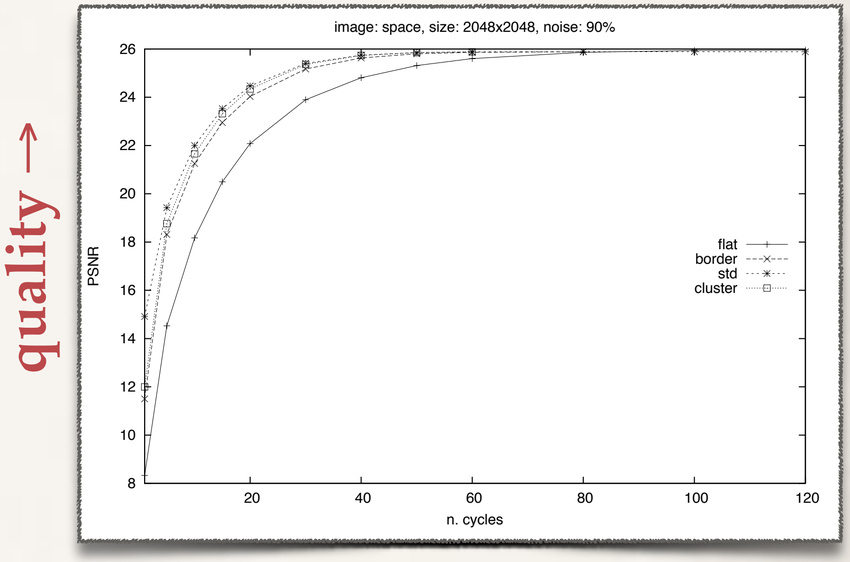
*Try any possible color **k** for the pixel, choose **u**, the one that minimize the value of F(neighb8(i,j))*

F(…) weight differently noisy and not noisy pixels

```
do
   foreach i,j
     if (noisyMap[i,j])
       let N = neighb8(img,i,j)
       let k in 0..255
         u=argmin(F(k,N,noiseMap))
       img[i,j]=u
while (process not converge)
```

Convergence can't be evaluated with a reduce (involves three iterations, i.e. memory)





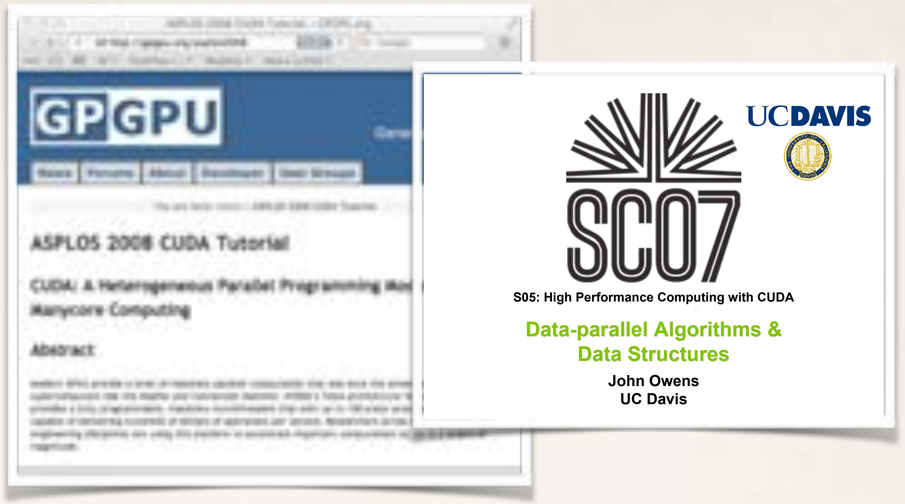
terminate if

$$\frac{\left|\left|\sum \Delta^{(k)}\right| - \left|\sum \Delta^{(k+1)}\right|\right|}{\left|\sum \Delta^{(k)}\right|} < \epsilon \in \mathcal{R}$$

M. Aldinucci, M. Drocco et al.
IJHPCA submitted

Patterns natural in GPGPUs

… and this week-known from long time



Think In Parallel

- The GPU is a data-parallel processor
  - Thousands of parallel threads
  - Thousands of data elements to process
  - All data processed by the same program
    - SPMD computation model
  - Contrast with task parallelism and ILP
- Best results when you "Think Data Parallel"
  - Design your algorithm for data-parallelism
  - Understand parallel algorithmic complexity and efficiency
  - Use data-parallel algorithmic primitives as building blocks

Data-Parallel Algorithms

- Efficient algorithms require efficient building blocks
- This talk: data-parallel building blocks
  - Map
  - Gather & Scatter
  - Reduce
  - Scan

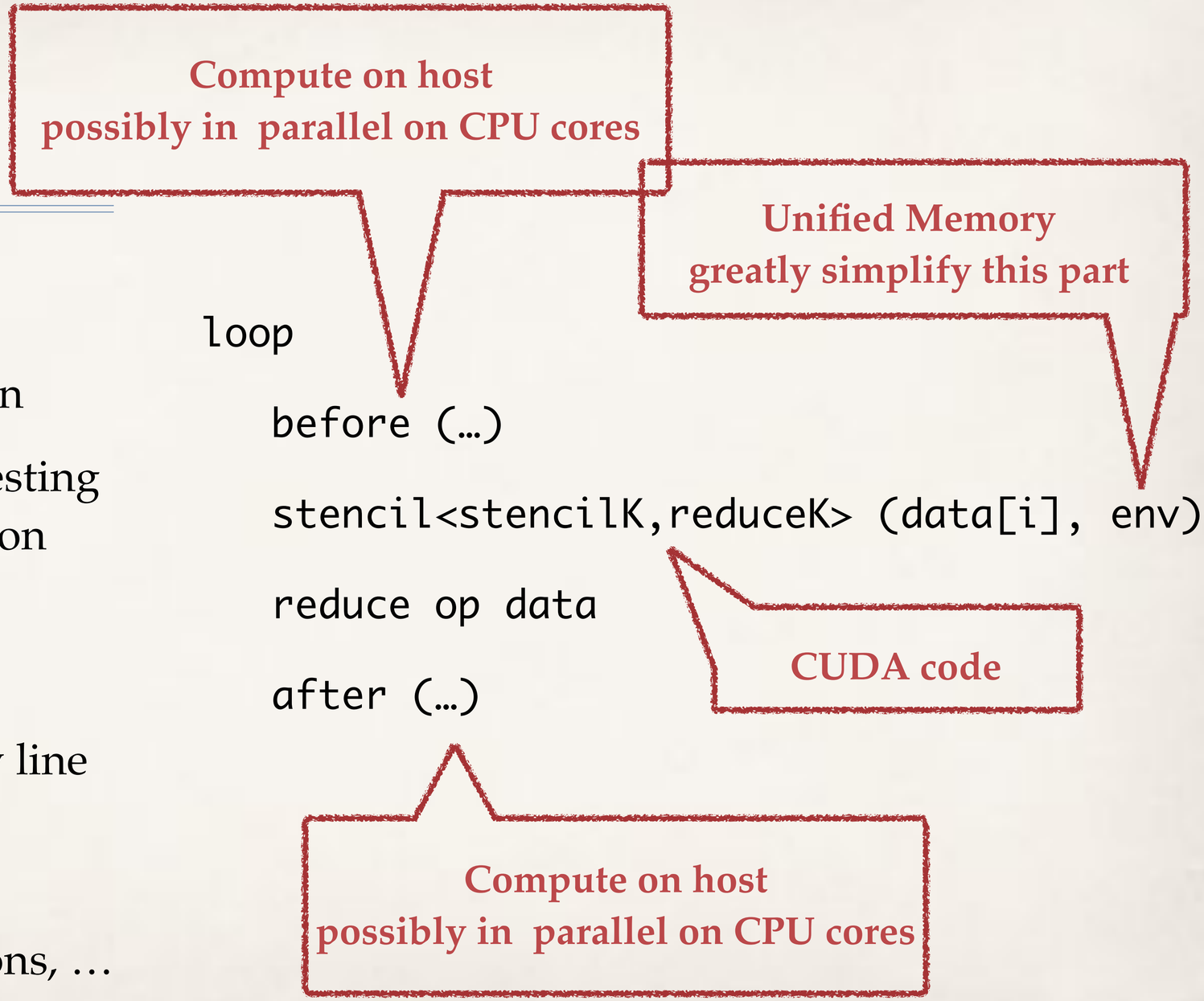
but are "standard" and "flat" data-parallel pattern expressive enough for the problems?

Rationale: patterns are there, but

- Detect-Denoise can be naturally pipelined
- Denoise is a (sort of) map with a stencil
  - Where, x = < x1, x2, …, xn >, map f x = < f(x1), f(x2), …, f(xn) >
  - Can be written as a map, but is neither natural nor easy
  - Try to think it without shared memory (halo management)
- Convergence evaluation is map across three iterations and reduce
  - Even more complex to write it as a MapReduce (if not impossibile)
- Cholesky LU or C4.5 tree pruning with map, reduce or MapReduce?

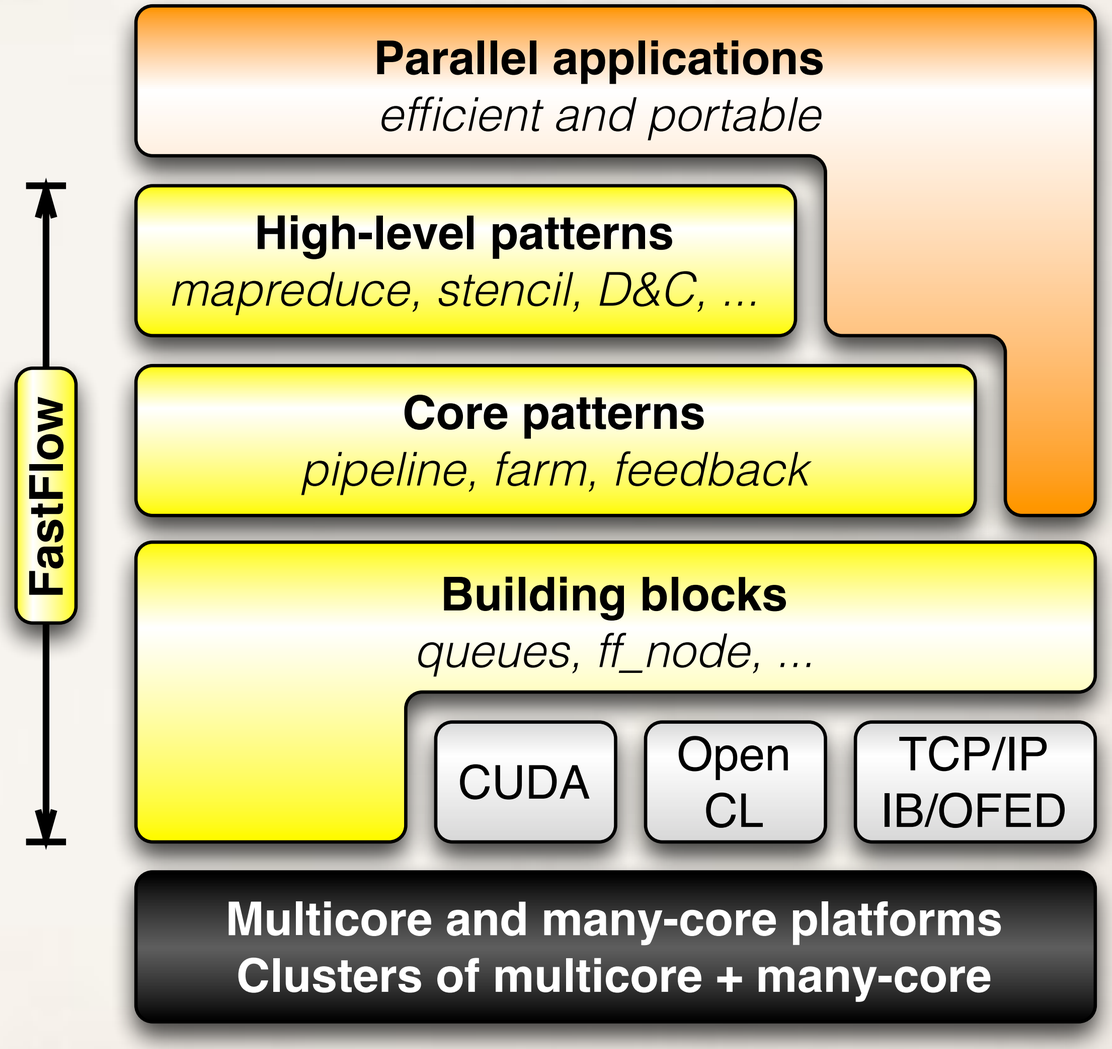
stencilReduce

- a (low-level) powerful pattern
  - presented here, need more validation
- we believe it capture most of the interesting data parallel computations, especially on GPGPUs
- Subsumes: map, reduce, mapReduce
- Programmers do not need to write any line of host code to drive the GPGPU
  - D2H/H2D, data feeding, synchronisations, block configurations, …

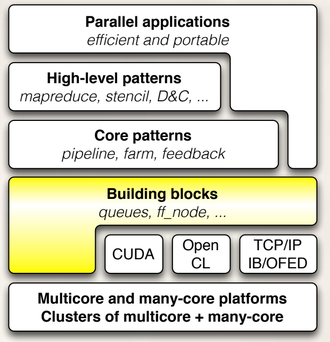


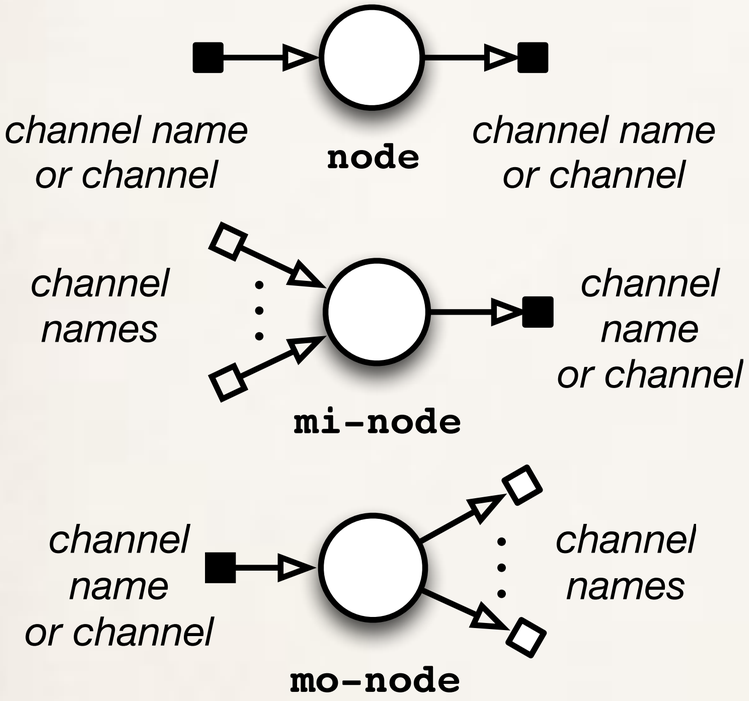
FastFlow (FF)

- C++ header-only library
  - Portable everywhere exists a C++ compiler (C++11 for some features)
- Provides stream-oriented and data-parallel patterns
  - compositional, efficient
- Accommodate diversity via progressive abstraction layers: if you need a different pattern, do it extending a C++ class
- Multi-core, GPGPUs, distributed
- `https://sourceforge.net/projects/mc-fastflow`



FF building blocks: nodes and channels





threads or processes
threads are non-blocking
(can be suspended using
a native protocol)

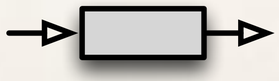
FF bound shmem FIFO channel

Single-Producer-Single-Consumer
lock-free fence-free queue

FF unbound shmem FIFO channel

Single-Producer-Single-Consumer
lock-free fence-free queue

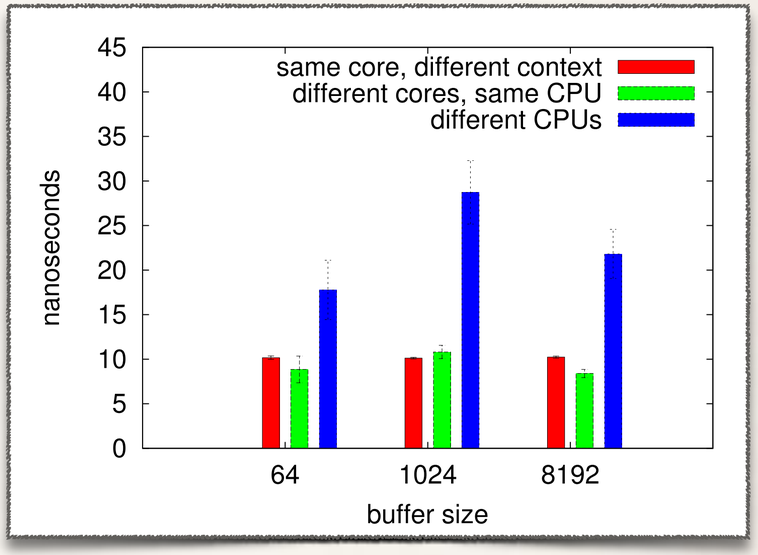
shmem channels communicate
pointers in a message passing style



Distributed zero-copy channel

0MQ/TCP or native IB/OFED

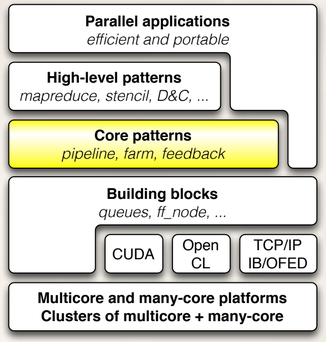
Xeon E7-4820 @2.0GHz Sandy Bridge

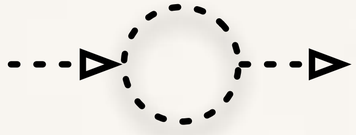


- MVAPICH ~ 190ns
- faster and more scalable than CAS/test-and-set implement.

M. Aldinucci and M. Danelutto and P. Kilpatrick and M Meneghin. An Efficient Synchronisation Mechanism for Multi-Core Systems. Euro-Par 2012. LNCS.

Semantics of the node: dataflow activation



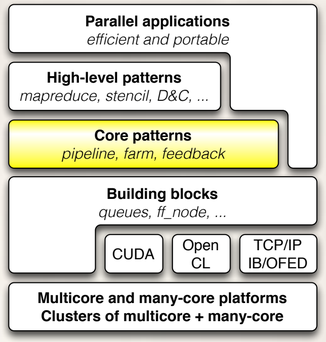


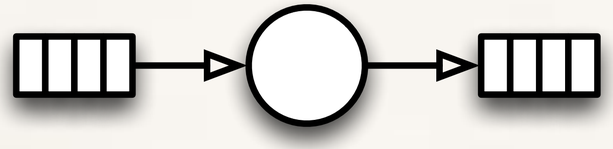
ff_node

mynode **is created as a standard C++ class extending** ff_node

```
class mynode: public ff_node {
public:
    int   svc_init() {
        /* after constructor - running as a thread */
        return 0;
    }

    void * svc(void * task) {
        int * t = (mytask_t *) task;
        // do something on task
        cout << “mynode "<< ff_node::get_my_id()
             << " received task " << t->payload << "\n";
        return task;
     }

    void  svc_end() {
        /* before destructor - running as a thread */
    }
};
```

Semantics of the node: dataflow activation





ff_node

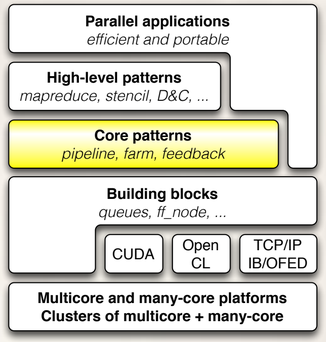
After class construction `mynode` **is turn into a thread**

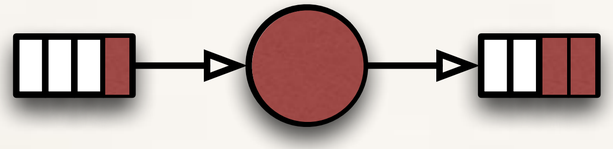
Nodes are not tasks (as in TBB), they are executors

The `svc_init()` **method is executed**

```
class mynode: public ff_node {
public:
    int   svc_init() {
        /* after constructor - running as a thread */
        return 0;
    }

    void * svc(void * task) {
        int * t = (mytask_t *) task;
        // do something on task
        cout << “mynode "<< ff_node::get_my_id()
             << " received task " << t->payload << "\n";
        return task;
     }

    void  svc_end() {
        /* before destructor - running as a thread */
    }
};
```

Semantics of the node: dataflow activation





ff_node

the node enters in a infinite loop

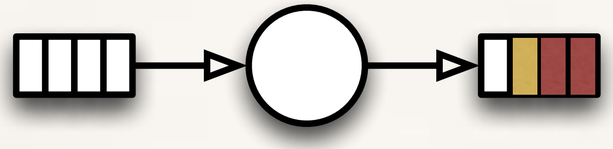
1. **get a task from input channel (i.e. a pointer)**
2. **execute `svc` method**
3. **put a task the output channel (i.e. a pointer)**

`svc()` might output more tasks via `ff_send_out` call (not shown)

The node terminate on returning a NULL pointer

```
class mynode: public ff_node {
public:
    int   svc_init() {
        /* after constructor - running as a thread */
        return 0;
    }

    void * svc(void * task) {
        int * t = (mytask_t *) task;
        // do something on task
        cout << “mynode "<< ff_node::get_my_id()
             << " received task " << t->payload << "\n";
        return task;
     }

    void  svc_end() {
        /* before destructor - running as a thread */
    }
};
```

Semantics of the node: dataflow activation



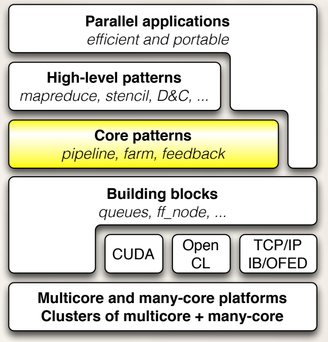
ff_node

svc_end **is executed before class destruction**

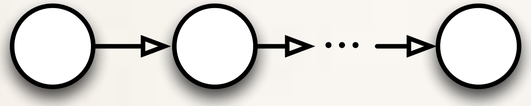
termination token is propagated to the next node

```
class mynode: public ff_node {
public:
    int   svc_init() {
        /* after constructor - running as a thread */
        return 0;
    }

    void * svc(void * task) {
        int * t = (mytask_t *) task;
        // do something on task
        cout << “mynode "<< ff_node::get_my_id()
             << " received task " << t->payload << "\n";
        return task;
     }

    void  svc_end() {
        /* before destructor - running as a thread */
    }
};
```

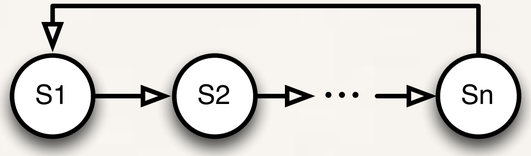
FF core patterns: pipe, farm, feedback
they are streaming networks, not task graphs



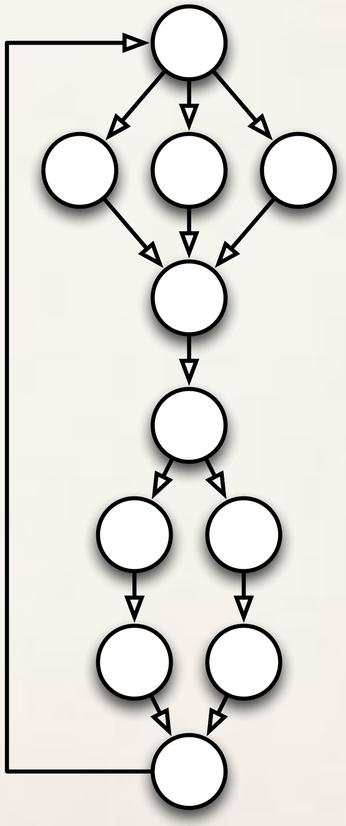
pipeline



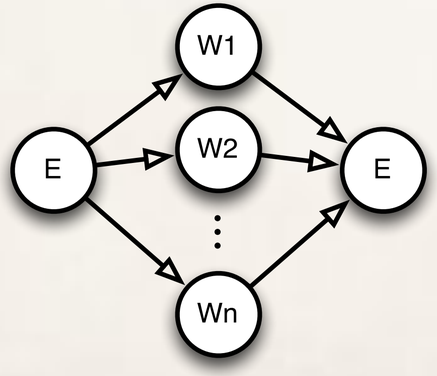
pipeline with feedback



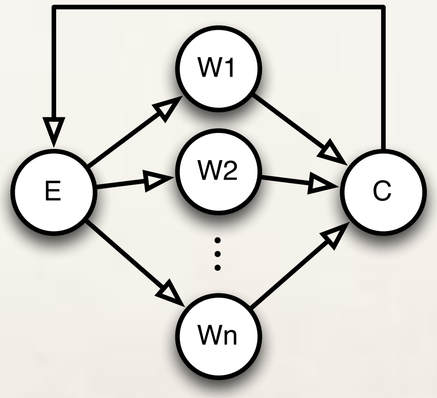
or any composition of them

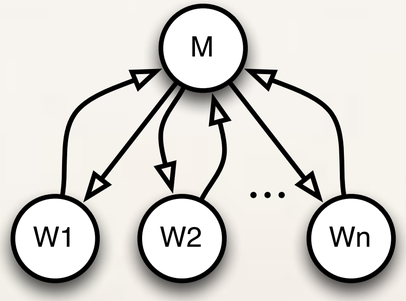


farm

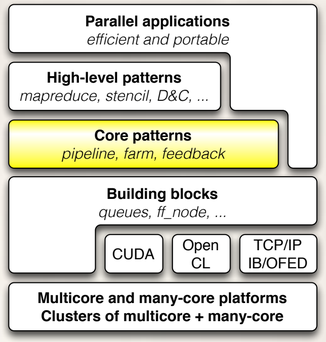


farms with feedback
(e.g. D&C and Master-Workers)

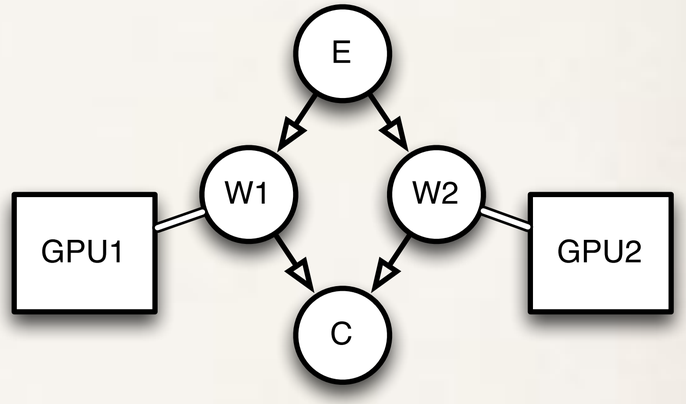




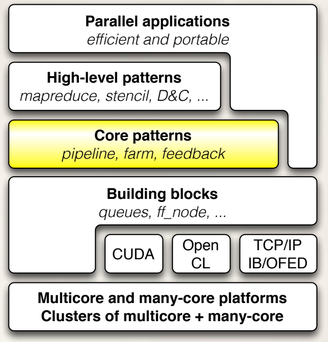
GPGPUs



- Fill stencilReduce methods with CUDA kernel code
  - No CUDA-related host code at all need to be written
- Possibly nest stencilReduce into another pattern
  - e.g. farm to use many GPGPUs
    - the async copy engine is automatically used via CUDA streams
  - Helpful to mix threading (or distributed) with GPGPUs
  - If you already have your standard host+CUDA code just copy-paste into a svc( ) method

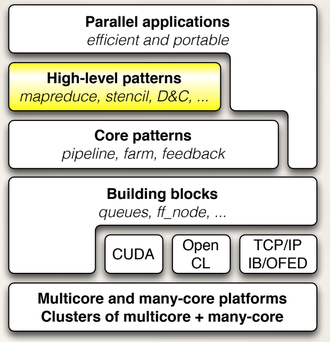


FF core patterns: rationale



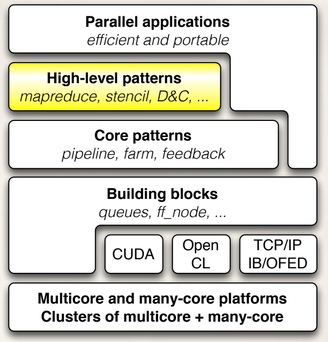
- farm: process in parallel independent tasks (e.g. C++ objects)
  - true dependencies are enforced only along edges of the graph
  - workers might synchronise (e.g. w locks/atomics), synchronisation in the business code
- farm, pipeline and feedback (to build cyclic networks) are enough to write all other patterns
- Think to GPGPUs design
  - They be though as machines to compute a map, reduce, stencil, …
  - … but in hardware they are built as a farm that dispatches independent blocks onto multiprocessors (+global memory)

FF high-level patterns



- Proposed as code annotations
  - Similarly to openMP, openacc, …
  - used to generate a graph at the core pattern level
- Examples
  - parallel_for
  - map, reduce, MapReduce, … (targeting GPGPUs)
  - and as many as you want: developing a new pattern is just developing a new class

Example: map (derived from stencilReduce)



- 2 GPGPUs on the same platform
  - nest a stencilReduce, map, reduce … into a (host) farm with 2 workers
- offload code onto distributed GPGPUs
  - nest a stencilReduce, map, reduce … into a (host) distributed farm with 2 workers
  - data serialisation is up to user, the framework just provides callback to do it
- In both cases
  - be sure that tasks are independent (otherwise you need another pattern)

Example: map (derived from stencilReduce)

```
FFMAPFUNC(mapF, unsigned int, in, return (in * 2));

class cudaTask: public baseCUDATask<unsigned int> {
public:
     void setTask(void* t) {
          if (t) {
               cudaTask *t_ = (cudaTask *) t;
               setInPtr(t_->in);      // match of data pointer H2D
               setOutPtr(t_->in);     // match of data pointer D2H
               setSizeIn(inputsize); // needed without Unified memory
          }
     }
     unsigned int *in, *out;
};

main () {
…
// put the input in task->in
FFMAPCUDA(cudaTask, mapF) *myMap = new FFMAPCUDA(cudaTask, mapF)(*task);
myMap->run_and_wait_end();
// result is in task->out
…
}
```

This is just a name to distinguish this kernel

This is CUDA code

Simple in this case, but any CUDA code is valid here
It will be compiled with NVCC

This is a macro

For multicore we use C++11 lambda. Theoretically possible to use Lambda for kernel code? (maybe with UnifiedMemory)

Example: Qt-mandelbrot (from Qt samples)

Original (sequential)

```
…
const int Limit = 4;
bool allBlack = true;
if (restart) break;
if (abort) return;

for (int y = -halfHeight; y < halfHeight; ++y) {


uint *scanLine =
     reinterpret_cast<uint *>(image.scanLine(y + halfHeight));
double ay = centerY + (y * scaleFactor);
…
}
private:
…
```

FastFlow (parallel)

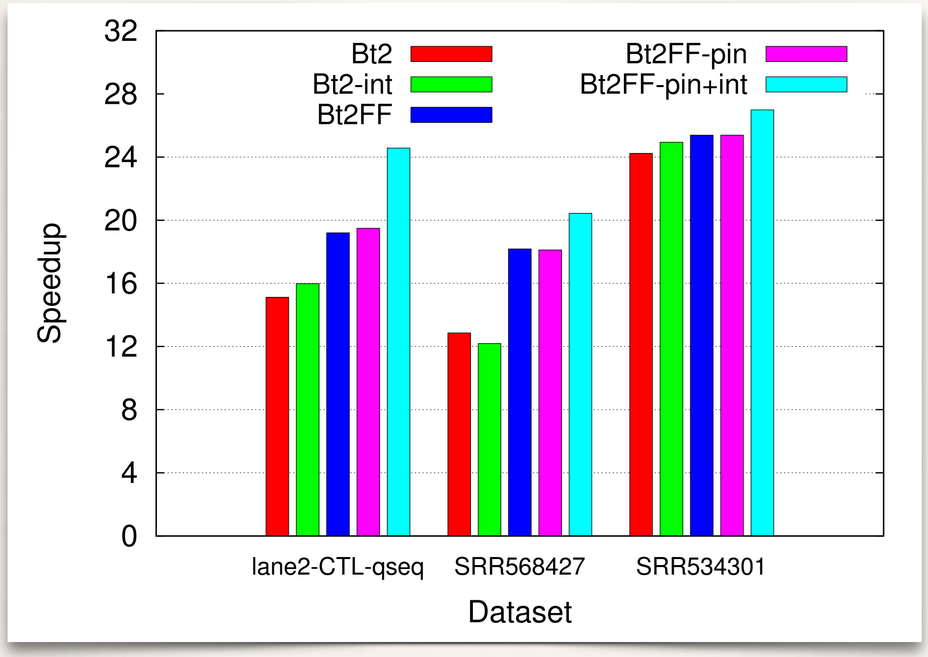
```
…
const int Limit = 4;
bool allBlack = true;
if (restart) break;
if (abort)   return;

pf_det.parallel_for(-halfHeight, halfHeight, 1, halfHeight,
                    [&](const long y) {
uint *scanLine =
     reinterpret_cast<uint *>(image.scanLine(y + halfHeight));
double ay = centerY + (y * scaleFactor);
…
}
private:
ParallelFor pf_det;
…
```

“Demo”

Don’t forget Murphy’s law

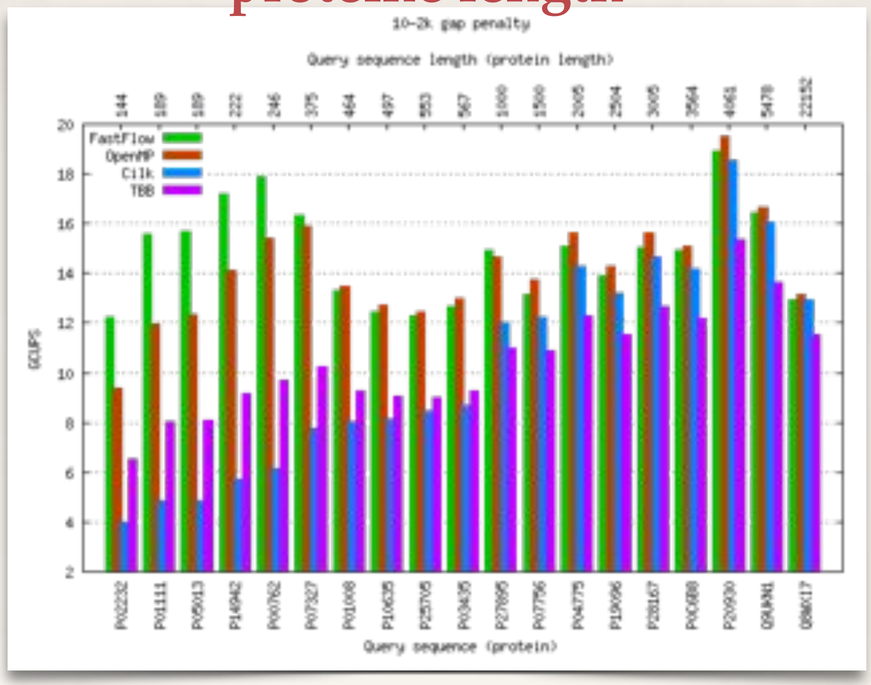
Performance (multicore)

Bowtie2 tool (DNA mapping)

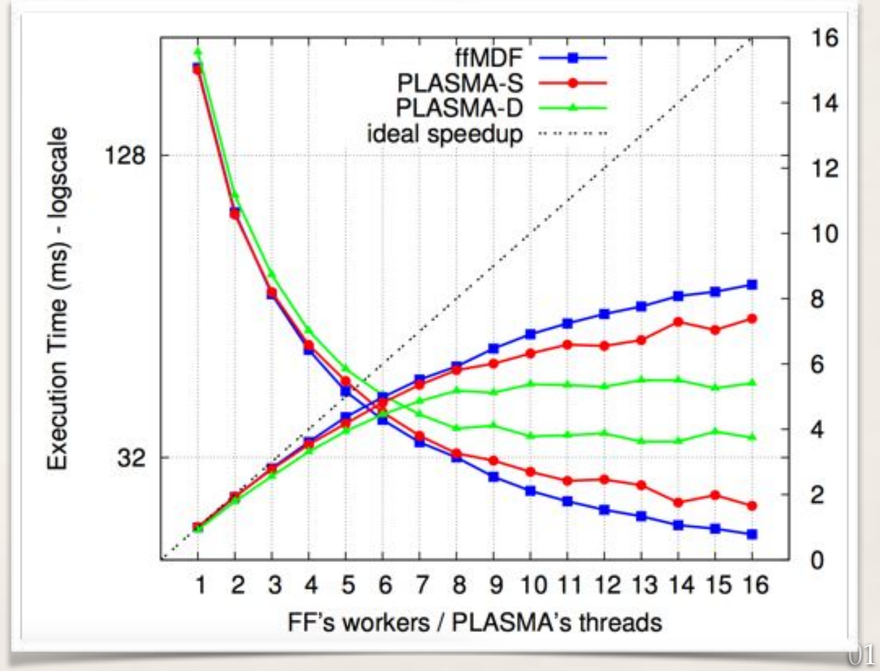


Original version: pthreads + test&set spinlocks
FF differs no more than 30 lines of
code from the original on several thousands
(including memory affinity management)

Smith-Waterman
(SSE2) against
OpenMP, Cilk, TBB

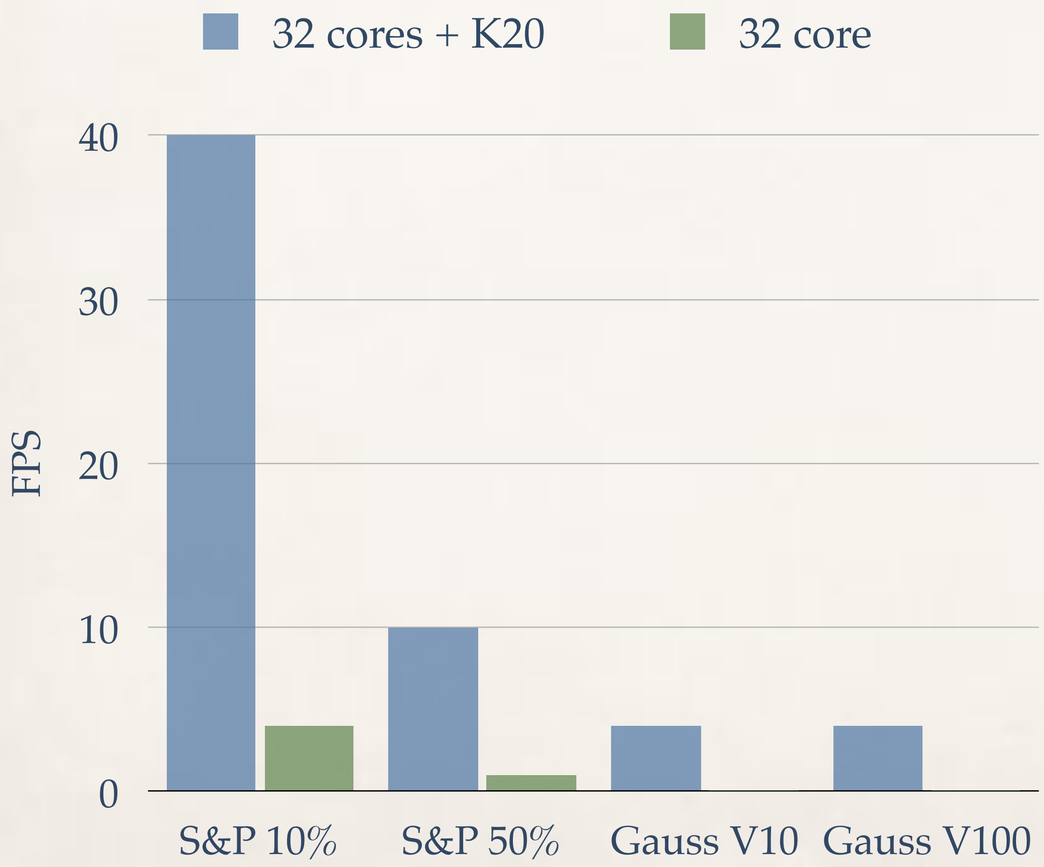


Cholesky LU
against PLASMA

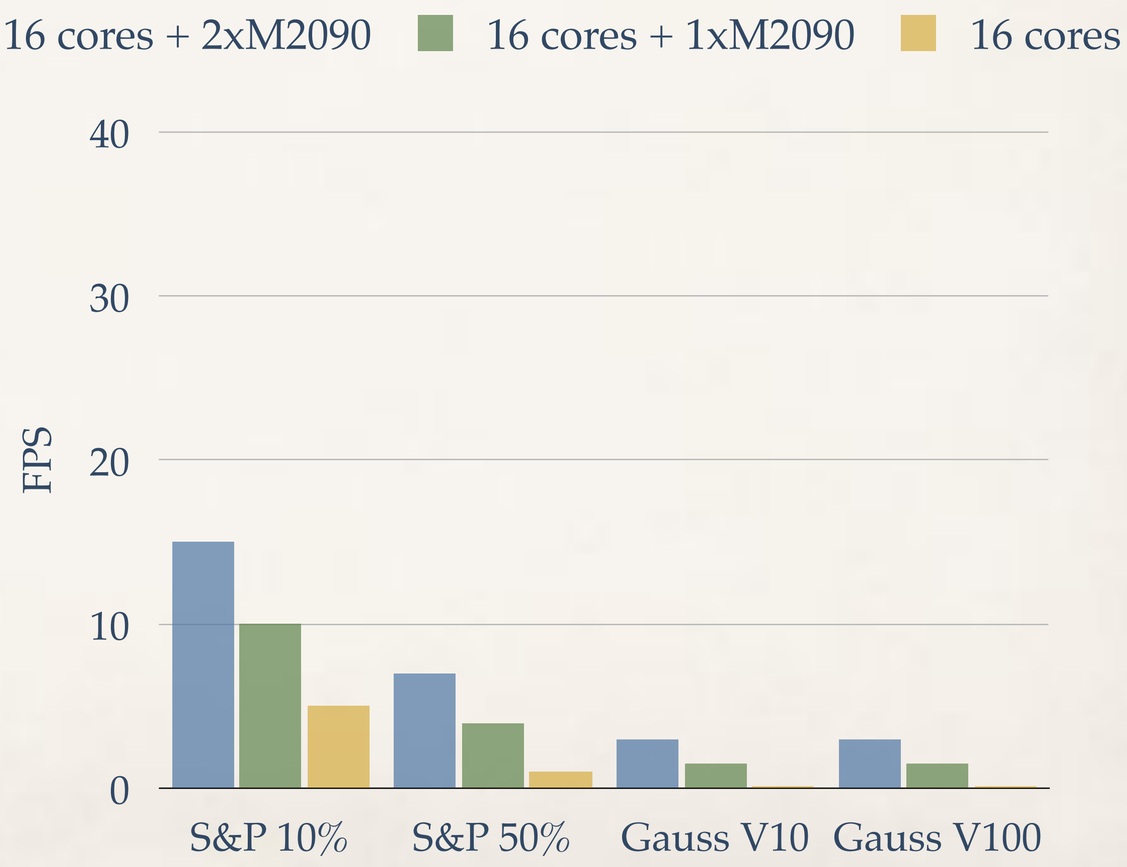


Performance (CPUs + GPGPUs)
Video frames 768x512

Nehalem 32 cores + 1 K20



SandyBridge 16 cores + 2 Tesla M2090



FastFlow: a framework for research

- Open-minded patterns
  - A pattern is missing? Not happy of the implementation? Modify it extending a class …
  - Multicore, GPGPUs, distributed under the same theoretical umbrella. No compilers to modify (!)
  - Non expert programmers does not need to deal with synchronisations and data copies, just select patterns
  - Productivity: portability, porting of legacy applications
- Comparable or better with OpenMP and TBB on fine grain
  - Comparable with OpenMP on data-parallel - really fast on streaming (especially very high-frequency)
- Entirely C++ (**C++11**), minimalistic design, solid enough to test new solutions
  - E.g. FastFlow lock-free parallel memory allocator extend with CUDA UnifiedMemory
  - Graceful optimisation curve: does not inhibits the optimisation of your kernel
- Main platform is Linux, but works almost everywhere exist a C++ compiler
  - MacOS, Win — x86, x86_64, Xeon Phi, PPC, Arm, Tilera, NVidia (CUDA and OpenCL) — gcc, clang, icc, nvcc

Coding details in the tomorrow talk:
S4585 - FastFlow: Combining Pattern-Level Abstraction and Efficiency in GPGPUs
Day: Wednesday, 03/26 - 15:00 - 15:50 - Room LL21A

University of Turin

M. Aldinucci

G. Peretti

A. Secco

F. Tordini

M. Drocco

C. Misale

University of Pisa

M. Torquati

M. Danelutto

EU-FP7 - 3.5M€

Unito - 440K€

EU-FP7 - 3.7M€

EU-FP7 Network of Excellence

`https://sourceforge.net/projects/mc-fastflow/`

3-years researcher positions available: deadline May 5, 2014
`http://www.di.unito.it/train2move/`