MiniLS → Streaming OpenMP → Work-Streaming

Albert Cohen [1]
Léonard Gérard [3] Cupertino Miranda [1] Cédric Pasteur [2]
Antoniu Pop [4] Marc Pouzet [2]
based on joint-work with Philippe Dumont [1,5] and Marc Duranton [5]

[1] INRIA
[2] ENS and Université Pierre et Marie Curie
[3] ENS and Université Paris-Sud
[4] Mines ParisTech
[5] while at Philips then NXP Semiconductors

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1. Terminology

Data-Flow Computing

Kahn networks

Least fixpoint of a system of equations over continuous functions on infinite streams

$\rightarrow$ Deterministic by definition

$\rightarrow$ $\equiv$ communicating processes over infinite FIFOs with blocking reads

Data-Flow Synchronous Computing

Synchronous semantics

Static restriction of Kahn semantics to zero-buffer equations, with clock types

- $\longrightarrow$ Communicating processes have the same logical clock
- $\longrightarrow$ Represents a sequential circuit
- $\longrightarrow$ Deadlock-free: causality analysis
- $\longrightarrow$ Static, clock-directed generation of sequential code

Data-Flow n-Synchronous Computing

[Cf. Synchron 2010 presentations of Louis Mandel and Florence Plateau.]

Goals

- Facilitate the programming of complex signal-processing algorithms
- Expose slack for desynchronization purposes and distributed/parallel execution
- Retain safety and performance (static compilation) properties

n-synchronous semantics

Static restriction of Kahn semantics to bounded buffer equations, with clock types

→ Communicating processes have synchronizable logical clock
  - Involves a richer algebraic structure on clock types
  - Synchronizability: $\bowtie$
  - Precedence: $\preceq$

→ Represent a latency-insensitive circuit

→ Static, clock-directed code generation
  - Translation to a ($\mathbf{0}$-)synchronous program
  - Or direct code generation to imperative code with buffers.

Stream Computing

1st interpretation: data-parallel Kahn networks

Data-flow computing where internal state is exposed as explicit (external) delays

$$\begin{array}{rcll} y = f(x) & \rightsquigarrow & (y, m) = f_{\text{pure}}(x, \texttt{pre}(m)) & \text{stateful} = \text{dependence distance } 1 \\ t = g(z) & \rightsquigarrow & (t, m) = g_{\text{pure}}(z, \texttt{pre}^k(m)) & \text{dependence distance } k \end{array}$$

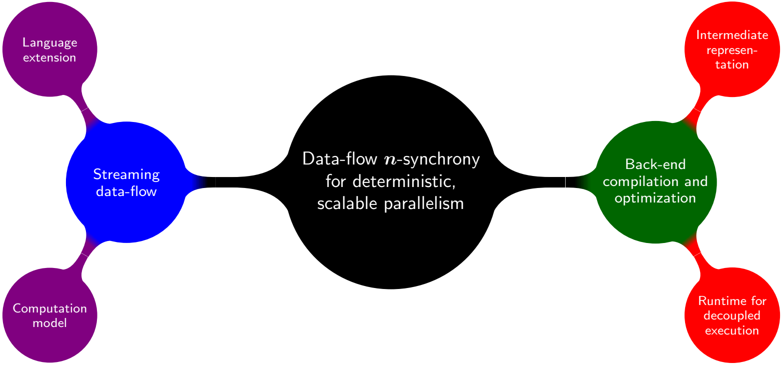
2nd interpretation: sliding window operations

Data-flow computing where past stream history is a first-class citizen in the syntax

- Reduces the need for states/delays in many algorithmic patterns
- Eliminates the associated copy overhead
- Syntactic sugar
- Express multi-token (bursty) reactions and asymmetric rate-conversions of CSDF [Cf. Synchron 2011 presentation of Leonard Gérard.]

2. Streaming Data-Flow n-Synchronous Programming

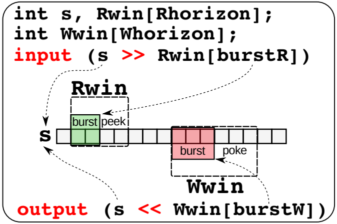
Directions of Work



3. Streaming Data-Flow n-Synchronous Extension of OpenMP

Streaming Data-Flow Programming

```
input/output (list)
    list   ::= list, item
             | item
    item   ::= stream
             | stream >> window
             | stream << window
    stream ::= var
             | array[expr]
    expr   ::= var
             | value
```



OpenMP 3.0 extensions [HiPEAC'11]

- Capture task-level, dynamic data flow
- Stream computing: sliding windows, rate conversion
  - Inspired by StreamIt
  - Richer abstractions for programming comfort
  - Avoids copy overhead and artificial introduction of state
- Working on n-synchronous semantics
- Target for the desynchronization of synchronous data-flow programs

New Clauses: `input` and `output`

```c
int x, z;
int X[horizon];
int A[3];

#pragma omp task input (x >> X[burst])
  // task code block
  // 2 < burst ⩽ horizon
  ... = ... X[2];

// array of 3 streams
#pragma omp task input (A[0] >> z)
  // task code block
  ... = ... z ...;

// stream with window horizon 3
#pragma omp task input (A)
  // task code block
  ... = A[0] + A[1] + A[2];
```

```c
int y;
int B[42][2];

#pragma omp task output (y)
  // task code block
  y = ...

// stream of arrays of size 2 with window horizon 42
#pragma omp task input (y >> B[17][])
  // task code block
  for (int i=0; i<17; ++i) {
    ... B[i][0];
    ... B[i][1];
  }
```

Interaction With Data Parallelism

```
#pragma omp parallel num_threads (2)
#pragma omp single
{
  for (i = 0; i < N; ++i) {
#pragma omp task firstprivate (i) output (o)
    o = work (i);
#pragma omp task input (o)
    more_work (o);
  }
}
```

```
#pragma omp parallel num_threads (2)
{
#pragma omp for
  for (i = 0; i < N; ++i) {
#pragma omp task firstprivate (i) output (o)
    o = work (i);
#pragma omp task input (o)
    more_work (o);
  }
}
```

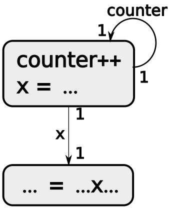
Interaction With Data Parallelism

```
#pragma omp parallel num_threads (2)
#pragma omp single
{
  for (p=head; p!=null; p=p->next) {
#pragma omp task firstprivate (p) output (o)
    o = work (p);
#pragma omp task input (o)
    more_work (o);
  }
}
```

```
#pragma omp parallel num_threads (2)
#pragma omp single
{
  for (p=head; p!=null; p=p->next) {
#pragma omp task firstprivate (p) output (o) num_threads (2)
    o = work (p);
#pragma omp task input (o)
    more_work (o);
  }
}
```

Stateful Filters

```
#pragma omp parallel
#pragma omp single
{
  int counter = 0;
  for (i = 0; i < N; ++i) {
#pragma omp task input (counter) output (x, counter)
    {
      counter++;
      x = ... ;
    }
#pragma omp task input (x)
    ... = ... x ...;
  }
}
```



Conditional Activation

```
for (i = 0; i < N; ++i) {
  if (condition_1 (i)) {
#pragma omp task firstprivate (i) output (x)
    x = i ;
  }
  if (condition_2 (i)) {
#pragma omp task firstprivate (i) input (x)
    y = x + i ;
  }
}
```

- Liveness?
- Boundeness?
- Is synchrony sufficient to solve the problem?

Delays

```
for (i = 0; i < M; ++i)
#pragma omp task output (x << A[k])
  for (j = 0; j < k; ++j)
    A[j] = ...;

  for (i = 0; i < N; ++i) {
#pragma omp task input (y) output (x)
    x = ... y ...;
#pragma omp task input (x) output (y)
    y = ... x ... ;
  }
```

- Stateless alternative to `pre`
- But liveness and boundeness requires n-synchrony

Interaction With Barriers

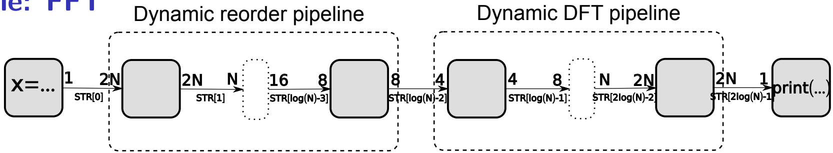
```
for (i = 0; i < M; ++i)
#pragma omp task output (x << A[k])
  for (j = 0; j < k; ++j)
    A[j] = ...;

#pragma omp taskwait
// deadlock if internal stream buffer size < kM

  for (i = 0; i < N; ++i) {
#pragma omp task input (y) output (x)
    x = ... y ...;
#pragma omp task input (x) output (y)
    y = ... x ... ;
  }
```

- Critically depends on n-synchrony!

More Combinations

- Nesting of parallel regions, tasks and work-sharing constructs
- Dynamic creation of tasks in (sequential or parallel) loops
- Variable burst size (with fixed horizon)

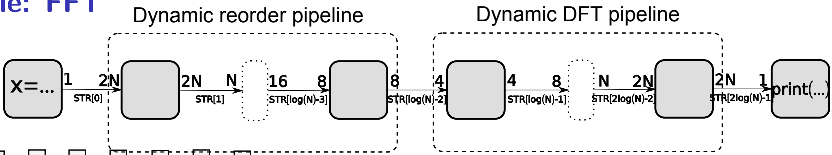
Example: FFT

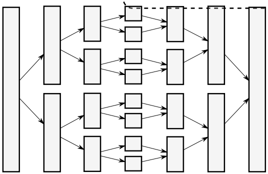



```
#pragma omp parallel
#pragma omp single
{
  float x, STR[2*(int)(log(N))];

  // Generate some input data
  for(i = 0; i < 2 * N; ++i)
#pragma omp task output (STR[0] << x)
    x = (i % 8) ? 0.0 : 1.0;

  // Reorder
  for(j = 0; j < log(N)-1; ++j) {
    int chunks = 1 << j;
    int size = 1 << (log(N) -j + 1);
#pragma omp task
    {
      float X[size];
      float Y[size];
      for (i = 0; i < chunks; ++i) {
#pragma omp task input (STR[j] >> X[size]) \
              output (STR[j+1] << Y[size])
        for (k = 0; k < size; k+=4) {
          Y[k/2] = X[k];
          Y[k/2+1] = X[k+1];
          Y[(k+size)/2+1] = X[k+2];
          Y[(k+size)/2+2] = X[k+3];
        }
  }}}
```

```
  // DFT
  for(j = 1; j <= log(N); ++j) {
    int chunks = 1 << (log(N) - j);
    int size = 1 << (j + 1);
#pragma omp task
    {
      float X[size], Y[size];
      float *w = compute_coefficients (size/2);

      for (i = 0; i < chunks; ++i) {
#pragma omp task input (STR[j+log(N)-2] >> X[size]) \
                 output (STR[j+log(N)-1] << Y[size]) shared (w)
        for (k = 0; k < size/2; k += 2) {
          float t_r = X[size/2+k]*w[k] - X[size/2+k+1]*w[k+1];
          float t_i = X[size/2+k]*w[k+1] + X[size/2+k+1]*w[k];
          Y[k] = X[k] + t_r;
          Y[k + 1] = X[k+1] + t_i;
          Y[size/2+k] = X[k] - t_r;
          Y[size/2+k+1] = X[k+1] - t_i;
        }
  }}}

  // Output the results
  for(i = 0; i < 2 * N; ++i)
#pragma omp task input (STR[2*log(N)-1] >> x)
    printf ("%f\t", x);
}
```

Example: FFT





Reorder stages DFT stages

```
// Reorder
for(j = 0; j < log(N)-1; ++j) {
  int chunks = 1 << j;
  int size = 1 << (log(N) -j + 1);
#pragma omp task
  {
    float X[size];
    float Y[size];
    for (i = 0; i < chunks; ++i) {
#pragma omp task input (STR[j] >> X[size]) \
              output (STR[j+1] << Y[size])
      for (k = 0; k < size; k+=4) {
        Y[k/2] = X[k];
        Y[k/2+1] = X[k+1];
        Y[(k+size)/2+1] = X[k+2];
        Y[(k+size)/2+2] = X[k+3];
      }
}}}
```

```
  // DFT
  for(j = 1; j <= log(N); ++j) {
    int chunks = 1 << (log(N) - j);
    int size = 1 << (j + 1);
#pragma omp task
    {
      float X[size], Y[size];
      float *w = compute_coefficients (size/2);

      for (i = 0; i < chunks; ++i) {
#pragma omp task input (STR[j+log(N)-2] >> X[size]) \
              output (STR[j+log(N)-1] << Y[size]) shared (w)
        for (k = 0; k < size/2; k += 2) {
          float t_r = X[size/2+k]*w[k] - X[size/2+k+1]*w[k+1];
          float t_i = X[size/2+k]*w[k+1] + X[size/2+k+1]*w[k];
          Y[k] = X[k] + t_r;
          Y[k + 1] = X[k+1] + t_i;
          Y[size/2+k] = X[k] - t_r;
          Y[size/2+k+1] = X[k+1] - t_i;
        }
  }}}

  // Output the results
  for(i = 0; i < 2 * N; ++i)
#pragma omp task input (STR[2*log(N)-1] >> x)
    printf ("%f\t", x);
}
```

4. High-Level Parallelizing Compilation of MiniLS

Aim for SPMD: Simplest Possible Modular Design

```
async node pipe (i1, i2) outputs (o1, o2)
  let
    o1 = a(i1);
    async x = f(i1, o1);
    o = g(x, i1 fby i2);
    o2 = b(o)
  tel

let (r1, r2) = pipe(42, 17)
```

↓

```
main() {
#pragma omp parallel
#pragma omp single
  {
    pipe.reset(42);

    while (true) {
      int r1, r2;
#pragma omp task output (r1, r2)
      pipe.astep(42, 17, &r1, &r2);
    }
  }
} // end main

obc a {
  method reset () ...
  method step (i1) ...
}

...
```

```
obc pipe {
  mem int i2;

  method reset (int i1) {
#pragma omp task firstprivate (int i1) output (int i2)
    i2 = i1; return i2;
  }

  method step (int i1, int i2) {
    ...
  }

  method astep (int i1, int i2, int *o1_p, int *o2_p) {
    int x, o;

#pragma omp task firstprivate (i1) output (o1)
    o1 = a.step(i1); // a.step: { o1 = a(i1); return o1; }

#pragma omp task firstprivate (i1) input (o1) output (x)
    x = f.step(i1, o1); // f.step: { x = f(i1, o1); return x; }

#pragma omp task input (i2, x) output (o2)
  {
    o = g.step(x, i2); // g.step: { o = g(x, i2); return o; }
    o2 = b.step(o); // b.step: { o2 = b(o); return o2; }
  } // end step
}
```

5. Low-Level Work-Streaming Compilation

Intermediate Representation for Stream Computing

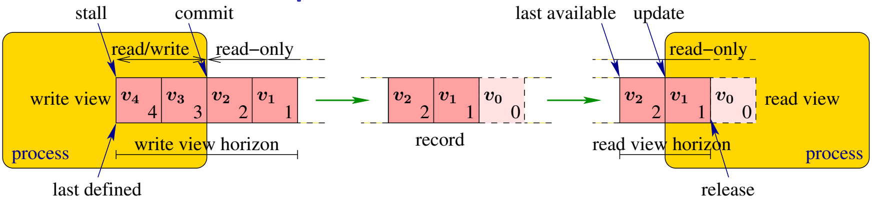
Question

Scalable and efficient compilation of data-flow streaming programs?

The three goals of Erbium [CASES'10]

1. Express deterministic multi-producer multi-consumer, task- and data-parallel computations
2. Eliminate runtime overhead, amortize hardware synchronization costs
3. Nothing to hide to the compiler
   - Decouple synchronization, communication, access to local buffers
   - Support aggressive scalar, loop and interprocedural optimization

Erbium Intermediate Representation and Runtime



- `record`: multi-producer, multi-consumer stream
- `view`: randomly addressable sliding window, read or write side
- `commit()`/`update()`: pressure
- `release()`/`stall()`: back-pressure
- `receive()`: one-sided, asynchronous communication
- Deterministic initialization protocol and garbage collection

Lightweight runtime

- Wait-free, consensus-free implementation: no hardware atomic instruction, no fence
- $\approx$ **10** cycles per streaming communication cycle
- Compatible with a work-stealing scheduler

Enables Task-Level Optimization

Important optimizations enabled by Erbium

- Conversion to persistent streaming processes
  - Scalable parallel execution of data-flow tasks with streaming constructs
- Task data-parallelization
  - Parallel iteration of independent activations of a task
  - Thread-level and vector parallelism
- Dynamic task coarsening
  - Sequential iteration of a task to hide latency
- Synchronization optimization
  - Elimination of redundant `update()`s/`stall()`s.

Some optimizations may be better handled at a higher semantical level

- Task fusion and scheduling
  - Static code generation, clock-directed
- Static task coarsening
  - Loop nest transformation analog: strip-mining

Work-Streaming Code Generation

Example: data-parallel task

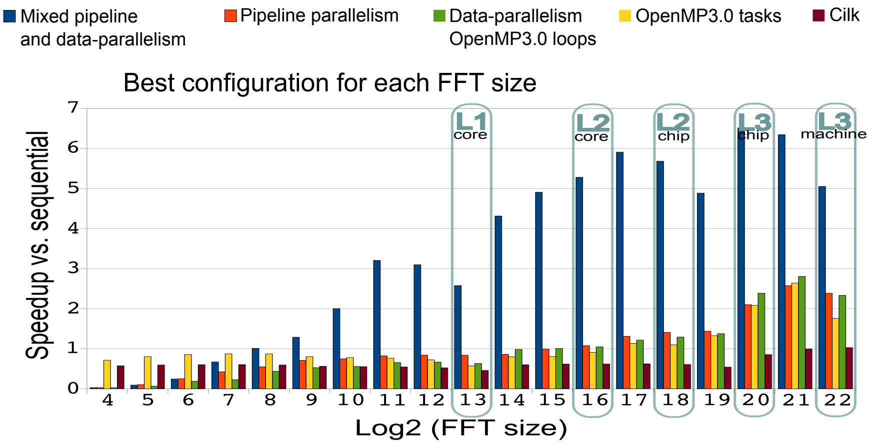
```
float x, y;
#pragma omp parallel for
for (...) {
  #pragma omp task input(x) output(y)
    y = f(x);
```

↓ Work-streaming compilation and runtime ↓

```
record float *s_x, *s_y;

init(s_x, ...);
init(s_y, ...);

allocate(s_x, ...);
allocate(s_y, ...);

for (i=0; i<nb_workers; i++)
  run persistent_task();
```

```
while(true) { // Code of a persistent streaming task
  int beg, end, beg_s, end_s;

  ask_for_work(s_x, &beg, &end); // work-stealing (blocking)

  for (beg_s=beg; beg_s<=end; beg_s+=AGGREGATE) {
    end_s = MIN(beg_s+AGGREGATE, end);
    stall(s_y, end_s); // blocking
    receive(s_x, beg_s, end_s); // non-blocking
    update(s_x, end_s); // blocking

    for (i=beg_s; i<end_s; i+=4)
      s_y[i..i+3] = f_v4f_clone(s_x[i..i+3]);
    for (max(0, i-4); i<end_s; i++)
      s_y[i] = f(s_x[i]);
    commit(s_y, end_s); // non-blocking
  }
}
```

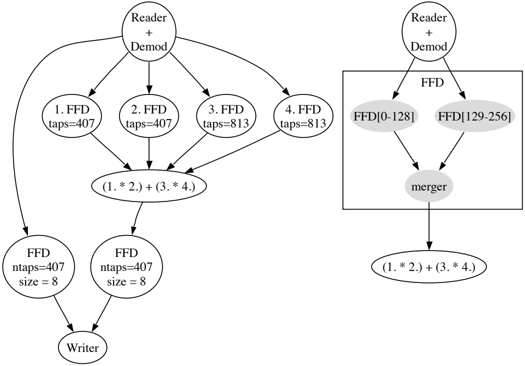
Application to FFT



4-socket Opteron – 16 cores

Combination of Task-Level and Low-Level Optimizations

Example: `fmradio` (from GNUradio)



Platform – cores	Seq. -O3	Par. -O2	Par. -O3	Par. -O3 vs. Par. -O2
Xeon – 24 cores	1.14	10.1	12.6	1.25
Opteron – 16 cores	1.52	9.51	14.6	1.54

6. Perspectives

What's Next?

- Definition of the n-synchronous semantics of the streaming extension
- Contributing to the OpenMP language specification
- Parallelizing compilation of n-synchronous Kahn networks
- Scalable parallelization with burst-synchronous Kahn networks
- Implementation of the work-streaming compilation algorithm
- Task-level optimization (coupled with polyhedral compilation)