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High-Performance SIMT Code Generation in an Active Visual Effects Library

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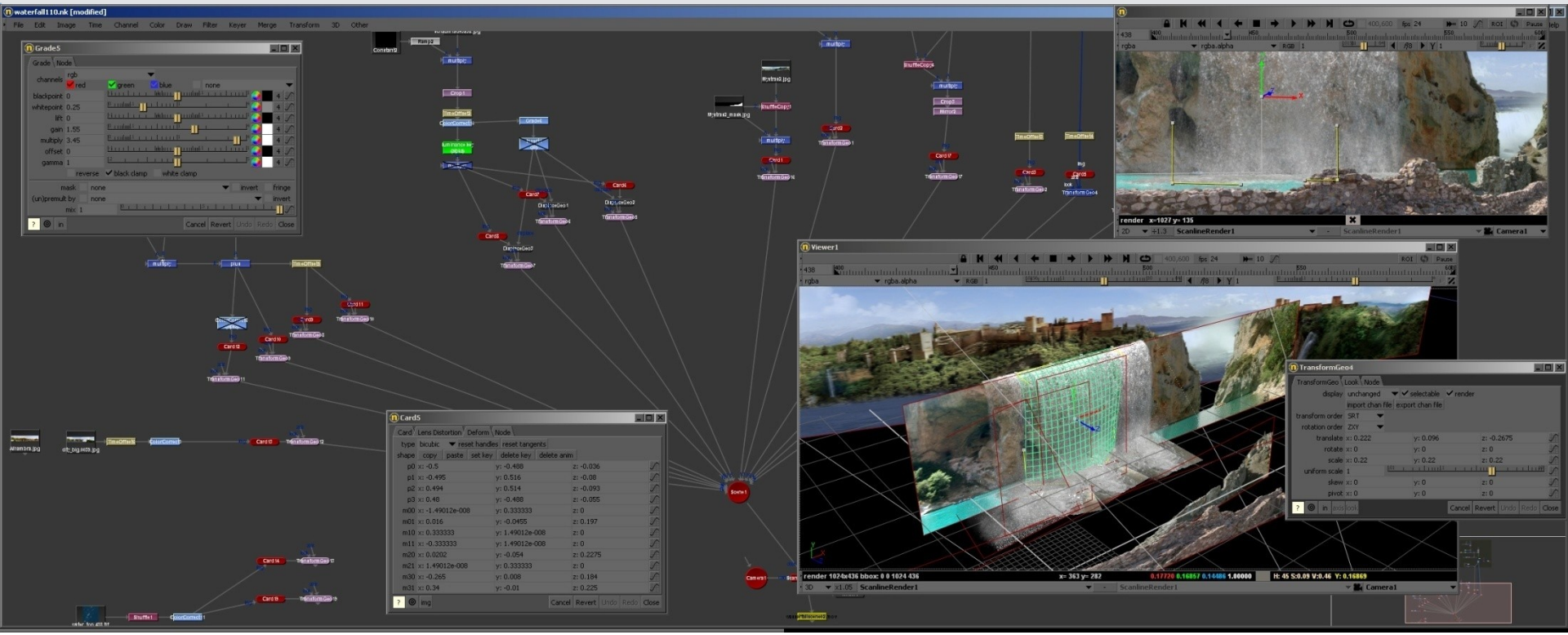
Visual effects in film post-production



- Nuke compositing tool (http://www.thefoundry.co.uk)
- Visual effects plugins appear as nodes in complicated effect graphs
- Execution time can be many seconds per frame

Visual effects kernels

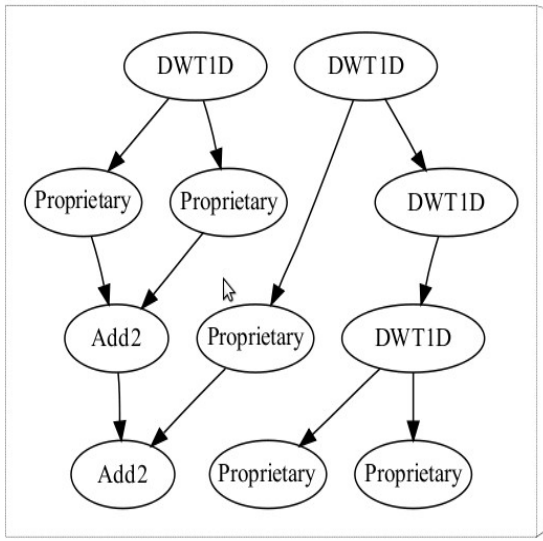
- **Kernels – individual image processing algorithms (data parallelism)**
  - Abstract computations
  - Iteration over images
  - Image memory access patterns
  - Action at each point in iteration space
  - Ordinary C++ which can be compiled and run on a CPU... *slowly*

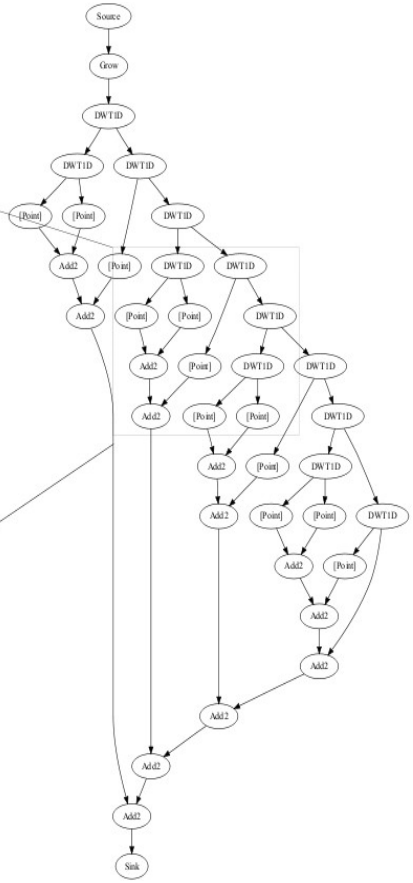
```
void DWT1D( float *input, float *highOutput, float *lowOutput, int radius ) {
 for( int y = 0; y < height; ++y ) {
  for( int x = 0; x < width; ++x ) {
   float centre = input[width*y + x];
   float high = (centre - (input[(width-radius)*y + x]
    + input[(width+radius)*y + x]) * 0.5f) * 0.5f;
   highOutput[width*y + x] = high;
   lowOutput[width*y + x] = centre – high;
  }
 }
};
```

Connecting kernels together

```
Image DeGrainRecurse(Image input, int level = 0) {
   Image HY,LY,HH,HL,LH,LL,HHP,HLP,LHP,LLP,pSum1,pSum2,output;

   DWT1D hDWT(eHorizontal, 1 << level);
   DWT1D vDWT(eVertical, 1 << level);
   hDWT(input, HY, LY);
   vDWT(HY, HH, HL);
   vDWT(LY, LH, LL);

   Proprietary prop;
   prop(HH, HHP);
   prop(LH, LHP);
   prop(HL, HLP);

   Sum sum;
   sum(HHP, LHP, pSum1);
   sum(HLP, pSum1, pSum2);

   /* Go to the next level of recursion. */
   LLP = (level < 3) ? DeGrainRecurse(LL, level+1) : LL;

   sum(pSum2, LLP, output);
   return output;
}
```

Delayed Evaluation





Why is a new approach necessary?

- **SIMD parallelism is difficult to exploit.**
  - Vectorising compilers are ineffective.
  - (Only **1 out of 9** of our algorithms were vectorised by Intel C/C++ 11.0.)
  - Hand-vectorisation is **difficult**, **error-prone** and raises **maintenance costs**.
  - We present a related solution for this problem in an upcoming publication.

- **SIMT parallelism is also difficult to exploit.**
  - SIMD hardware with a parallel programming model – which requires the programmer to think in SIMD terms to get any performance.
  - Isolating sufficient parallelism (**10000s of in-flight "threads"**) without compromising **spatial locality** is challenging.
  - Data movement through the memory hierarchy requires **micromanagement**.
  - Hand-parallelisation is **difficult**, **error-prone** and raises **maintenance costs**.

- **Building a compiler to do this is tricky.**
  - Our innovation instead lies in **metadata** – to bypass tricky code analysis.

Our approach: visual effects functors

- **A single-source C++ programming model.**
  - Minimises maintenance costs through a **write-once** paradigm.
  - Separates the **iteration schedule** from the algorithm.
  - Carries **metadata annotations**. (Underlined, more on these in a minute.)

```
class DWT1D : public Functor<DWT1D, eParallel> {
   Indexer<eInput, eChannel, e1D> Input;
   Indexer<eOutput, eChannel, e0D> HighOutput;
   Indexer<eOutput, eChannel, e0D> LowOutput;
   mFunctorIndexers(Input, HighOutput, LowOutput);

   DWT1D(Axis axis, Radius radius) : Input(axis, radius) {}

   void Kernel() {
      float centre = Input();
      float high = (centre - (Input(-Input.Radius) + Input(Input.Radius)) * 0.5f) * 0.5f;
      HighOutput() = high;
      LowOutput() = centre - high;
   }
};
```

Static Metadata

Discrete Wavelet Transform

Dynamic Metadata

Data-Parallel Kernel

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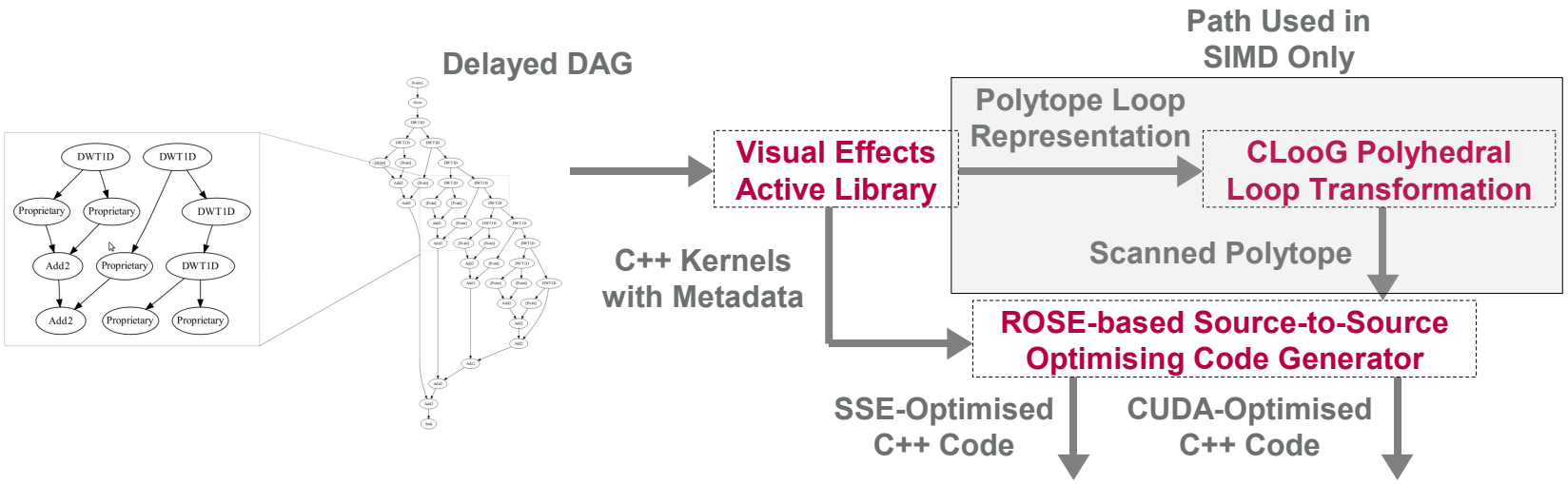
Our approach: visual effects functors

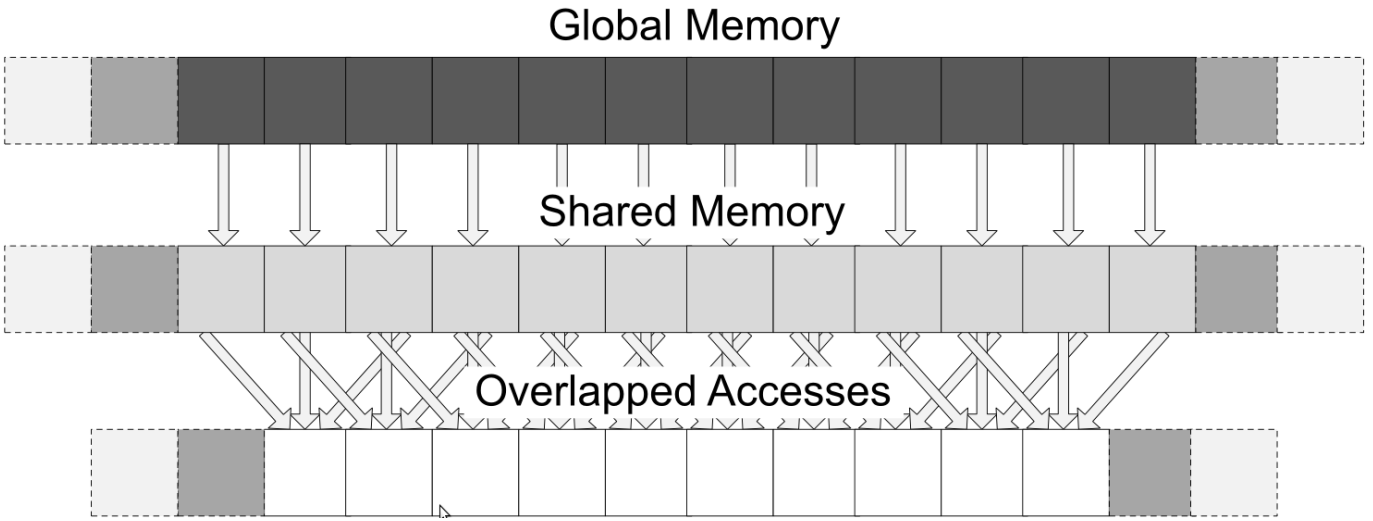
- **Programming model that supports *focused* and *maintainable* optimisations.**
  - Isolating the performance expertise to HPC developers, away from kernel authors
- **An optimising source-to-source code generator.**
  - Based on the ROSE **source-to-source** compiler framework.
  - **SIMD** and **SIMT** code generation backends.
  - A set of backend-specific **optimising code transformations**.



SIMT code is useless without optimisation

- **Shared memory staging.**
  - Localise overlapped access into **fast levels** of the memory hierarchy.
  - Each thread stages **one element** from global memory into *shared memory*.
  - Following **barrier synchronisation**, threads work from shared memory.

- **Metadata provides explicit information to make this trivial.**
  - Bypasses tricky code analysis.



DWT - metadata

- The kernel will be executed at each point in the iteration schedule.

```
void DWT( Image<float> input,
 Image<float> highOutput, Image< float > lowOutput
 int radius )
{

 for( int j = 0; j < height; ++j ) {
  for( int i = 0; i < height; ++i ) {
   float centre = Input( i, j );
   float high = (centre –
    ( input( i, j-radius )
    + input( i, j-radius ) * 0.5f) * 0.5f;

    highOutput( i, j ) = high;
    lowOutput( i, j ) = centre - high;
  }
};
```

```
class DWT1D : public Functor<DWT1D, eParallel> {
   Indexer<eInput, eChannel, e1D> Input;
   Indexer<eOutput, eChannel, e0D> HighOutput;
   Indexer<eOutput, eChannel, e0D> LowOutput;
   mFunctorIndexers(Input, HighOutput, LowOutput);

   DWT1D(Axis axis, Radius radius) : Input(axis,
radius) {}

   void Kernel() {
      float centre = Input();
      float high = (centre – (Input(-Input.Radius)
         + Input(Input.Radius)) * 0.5f) * 0.5f;
      HighOutput() = high;
      LowOutput() = centre - high;
   }
};
```

DWT – dependence metadata

- **Dependence metadata is key to manipulating the iteration schedule.**
  - A kernel can be **embarrassingly parallel** or have a **loop-carried dependence**.

```
void DWT( Image<float> input,
 Image<float> highOutput, Image< float > lowOutput
 int radius )
{

 for( int j = 0; j < height; ++j ) {
  for( int i = 0; i < height; ++i ) {
   float centre = Input( i, j );
   float high = (centre –
    ( input( i, j-radius )
    + input( i, j-radius ) * 0.5f) * 0.5f;

    highOutput( i, j ) = high;
    lowOutput( i, j ) = centre - high;
  }
};
```

```
class DWT1D : public Functor<DWT1D, eParallel> {
   Indexer<eInput, eChannel, e1D> Input;
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   Indexer<eOutput, eChannel, e0D> LowOutput;
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   DWT1D(Axis axis, Radius radius) : Input(axis,
radius) {}

   void Kernel() {
      float centre = Input();
      float high = (centre – (Input(-Input.Radius)
         + Input(Input.Radius)) * 0.5f) * 0.5f;
      HighOutput() = high;
      LowOutput() = centre - high;
   }
};
```
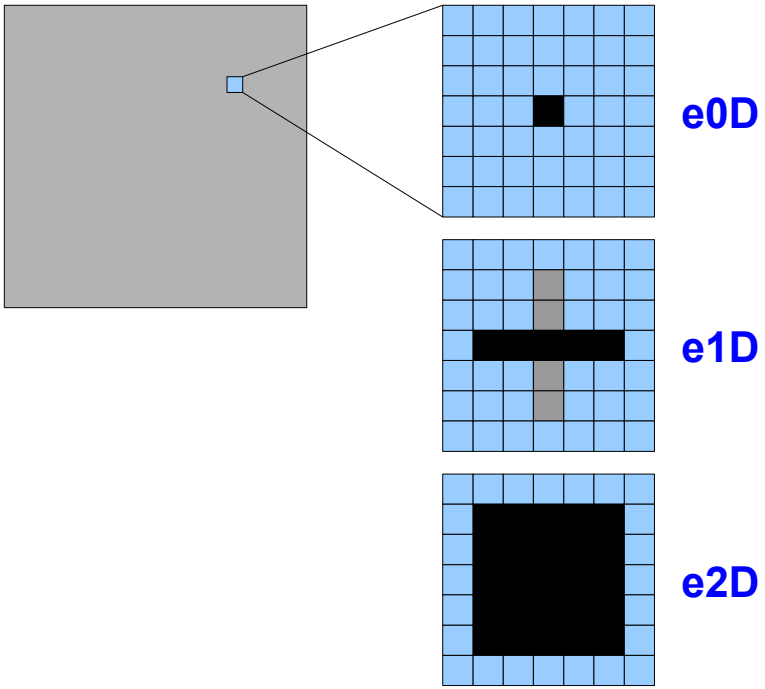

DWT – memory access metadata

- **Memory access metadata is key to managing data movement and sharing.**
  - To compute **one element** of output, how much input does the kernel need?
  - Red, green and blue together (**ePixel**) or one plane at a time (**eChannel**).
  - One element (**e0D**), a bounded line (**e1D**) or a bounded rectangle (**e2D**).




```
class DWT1D : public Functor<DWT1D, eParallel> {
   Indexer<eInput, eChannel, e1D> Input;
   Indexer<eOutput, eChannel, e0D> HighOutput;
   Indexer<eOutput, eChannel, e0D> LowOutput;
   mFunctorIndexers(Input, HighOutput, LowOutput);

   DWT1D(Axis axis, Radius radius) : Input(axis,
radius) {}

   void Kernel() {
      float centre = Input();
      float high = (centre – (Input(-Input.Radius)
         + Input(Input.Radius)) * 0.5f) * 0.5f;
      HighOutput() = high;
      LowOutput() = centre - high;
   }
};
```

Box blur - dependence metadata

- **An example of a kernel with a loop-carried dependence.**
  - Note that this dependence is algorithmic, it is not inherent in the computation.

```
void boxBlurV( Image< float > input,
   Image< float  > output ) {
 for( int j = 0; j < width; ++j ) {
   float movingSum = 0.0f;
   for( int r = -radius; r < radius; ++r )  {
     movingSum += input( r, 0 );
   }
   output( i, 0 ) = movingSum;
   for( int i = 1; i < height; ++i ) {
     movingSum += input( i – radius - 1, j ) +
       input( i + radius, j );
     output( i, j ) = movingSum * muliplier;
   }
};
```

```
•class BoxBlur : public Functor<BoxBlur, eMoving> {
   ...
   BoxBlur(Axis axis, int radius)
      : Functor<BoxBlur, eMoving>(axis),

   void Initialise() {
      MovingSum = 0.0f;
      for(int i = -Input.Radius; i <= Input.Radius; ++ i)
         MovingSum += Input(i);
   }

   void Kernel() {
      MovingSum = MovingSum
         - Input(-Input.Radius-1) + Input(Input.Radius);
      Output() = MovingSum * MultBy;
   }

   const float MultBy;
   float MovingSum;
};
```

State Written (At iteration *i*)

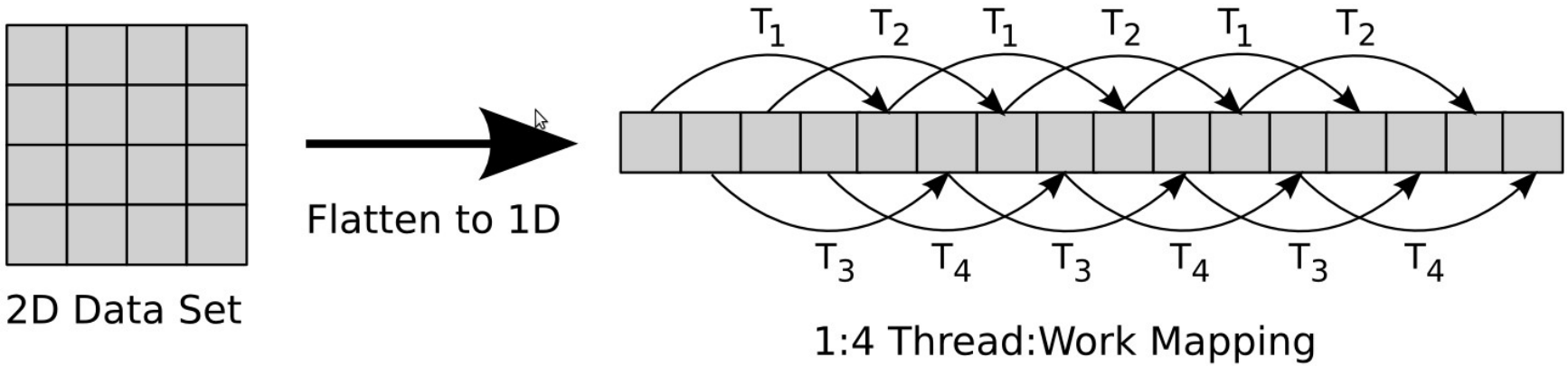
State Read (From iteration *i-1*)

Loop-Carried True Dependence

Inter-Iteration Modifiable State

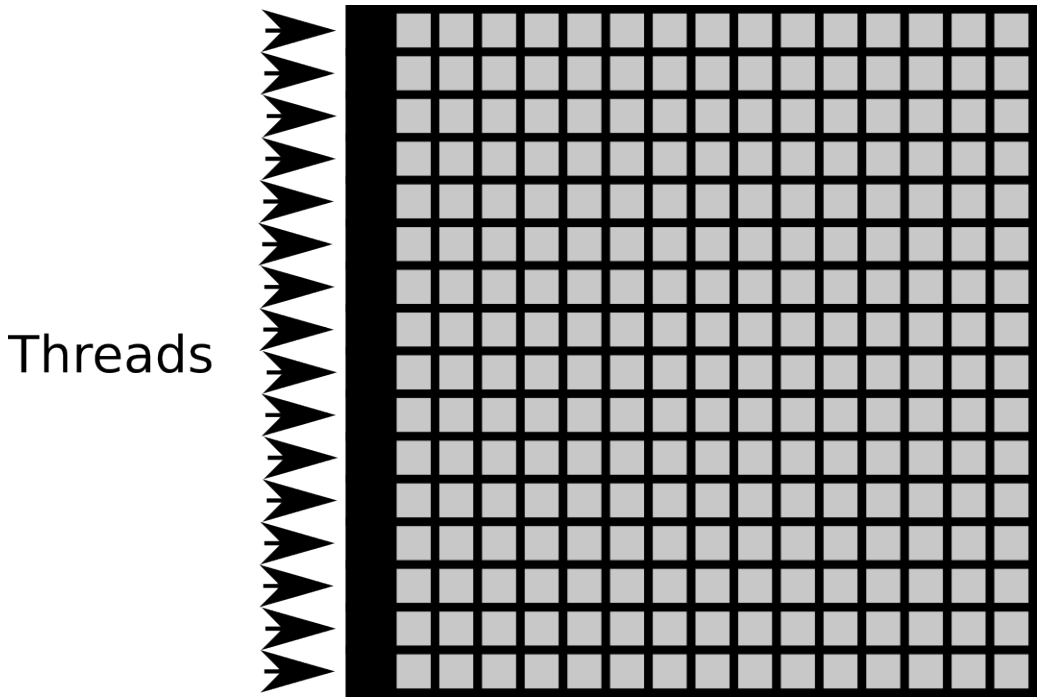
SIMT Optimisations – Block minimisation

- **Thread block minimisation.**
  - In simpler kernels, **thread scheduling overheads** can dominate.
  - One thread per pixel in a 4096x2304 image: **9.4M** threads.
  - A mapping of **N** output pixels to a single thread can alleviate this overhead.



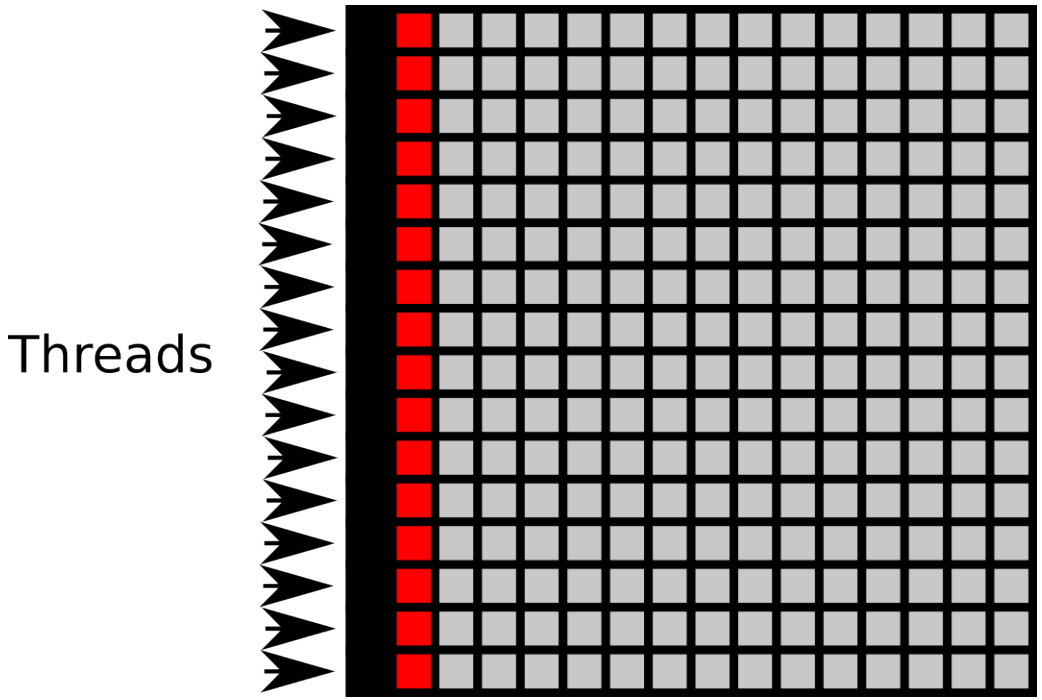
SIMT Optimisations – horizontal rolling filters

- Threads move horizontally through the data



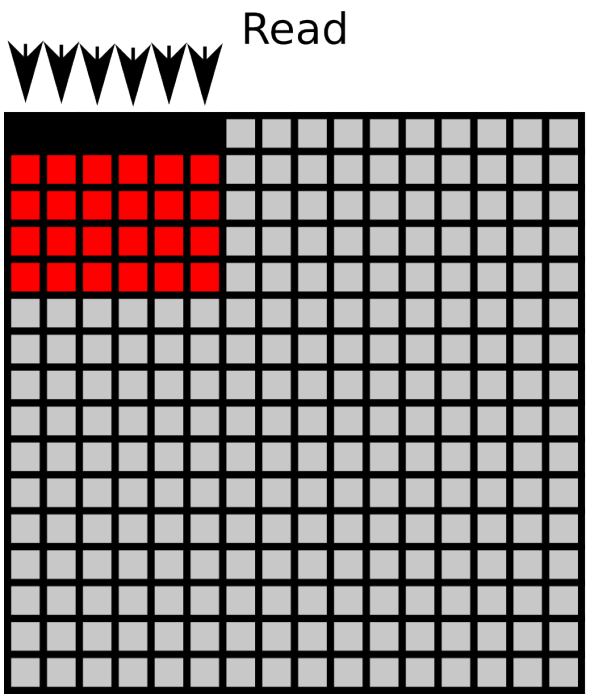
SIMT Optimisations – horizontal rolling filters

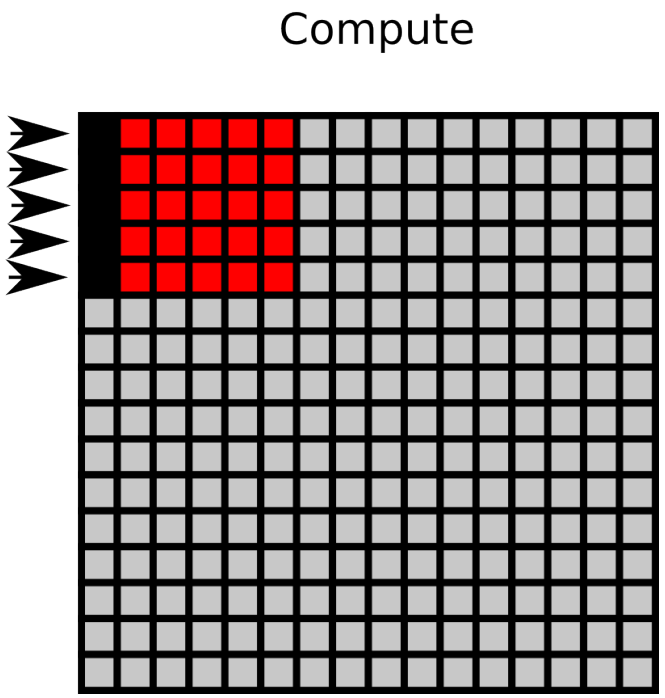
- **Threads move horizontally through the data**
- **Reads are vertical**
  - Inefficient, non-contiguous.



SIMT Optimisations – horizontal rolling filters

- **Threads move horizontally through the data**
- **Reads are vertical**
  - Inefficient, non-contiguous.
- **Solve by reading a block**
  - Limited shared memory makes this inefficient for a large number of threads.

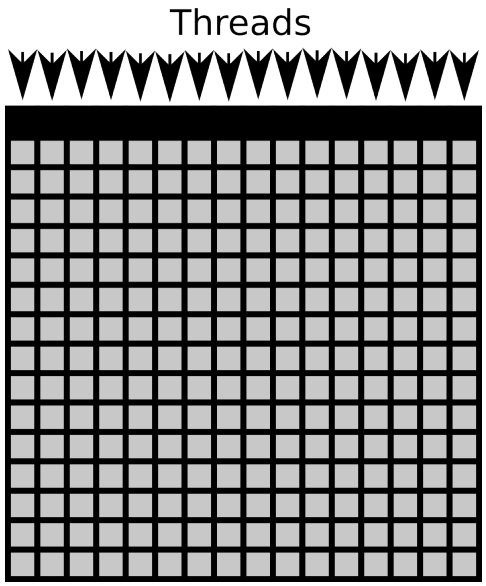




SIMT Optimisations - Transposition

- **Alternatively we can:**
  - Transpose the dataset.
  - Make parallelism horizontal again, so reads are efficient.

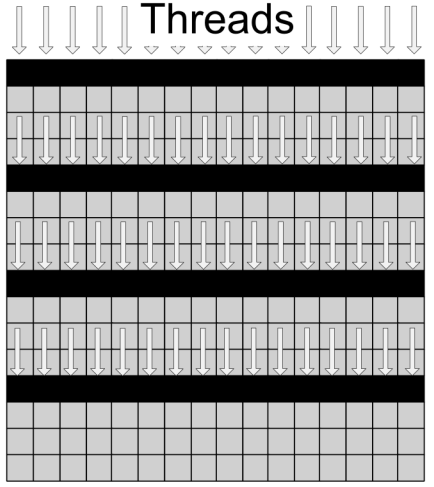
- **Transposition is as easy as adding transpose nodes to the DAG.**
  - A post-optimisation looks for adjacent **pairs of transpositions** and remove them.
  - Thanks to **DAG metadata**.



SIMT Optimisations – Split row/column

- **Split row/column parallelism.**
  - Algorithms which are serialised in one axis may not be parallel enough.
  - GPUs keep **1000s** of threads in flight – images are not usually that **wide** or **tall**.
  - Parallelism can be "created" by *initialising* a new serialised run part-way.
  - Then **one thread** per axis becomes **two**, **three**, **four**, … with a small overhead.

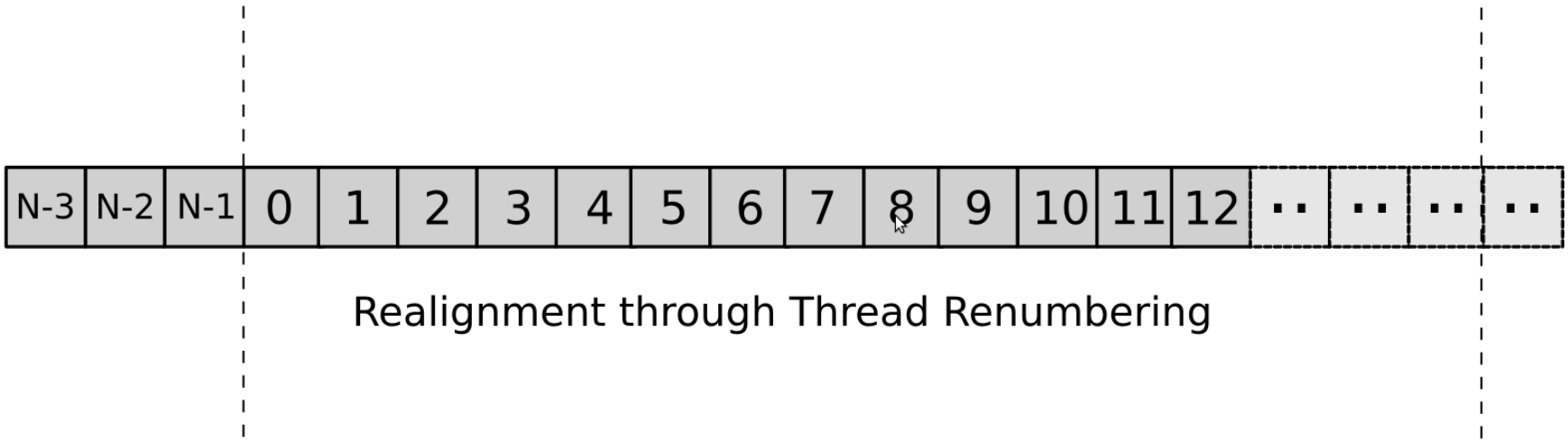
```
class BoxBlur : public Functor<BoxBlur, eMoving> {
   ...
   void Initialise() {
      MovingSum = 0.0f;
      for(int i = -Input.Radius; i <= Input.Radius; ++ i)
         MovingSum += Input(i);
   }
   ...
};
```



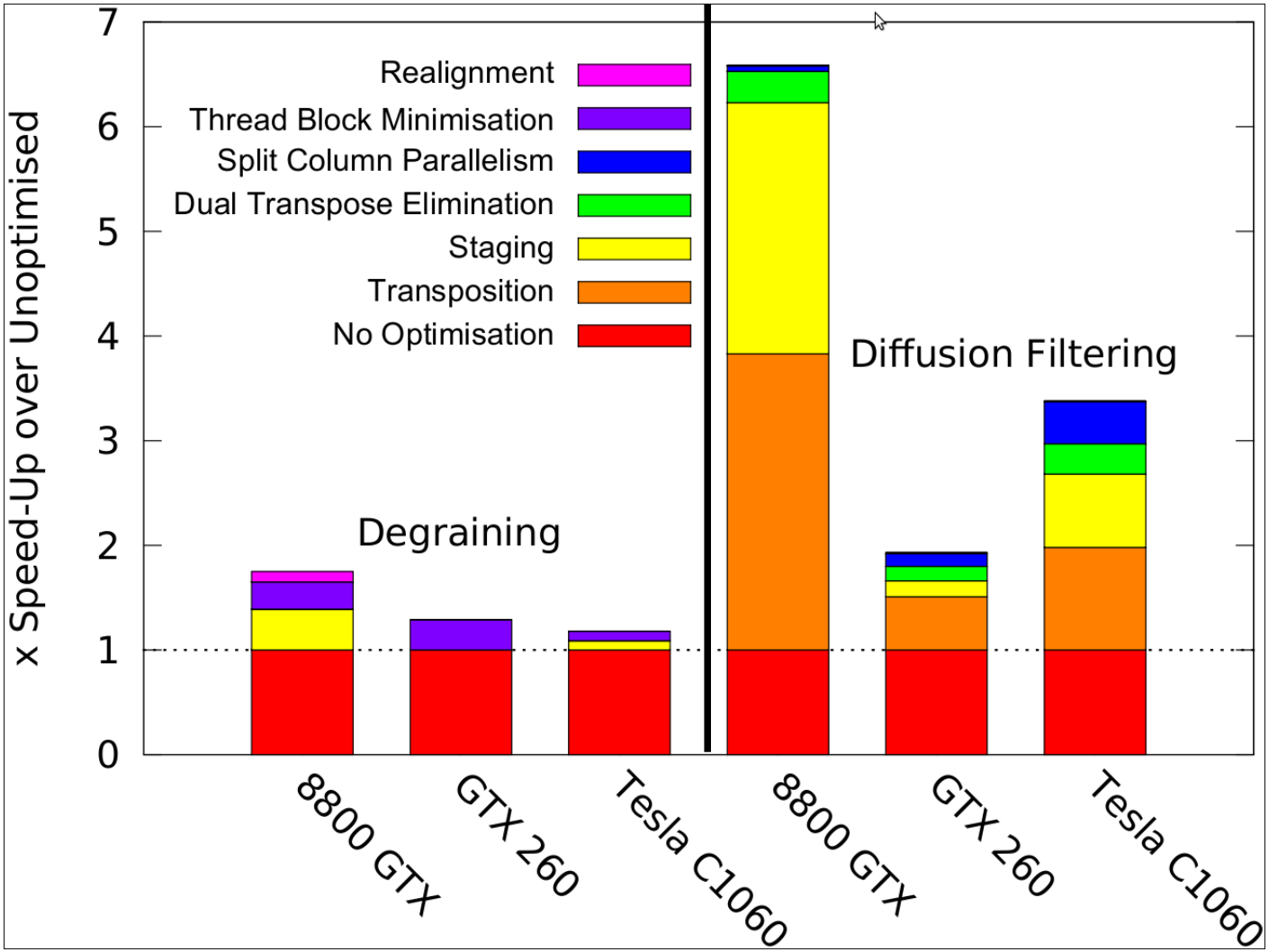
Split Column Parallelism

SIMT Optimisations – Access realignment

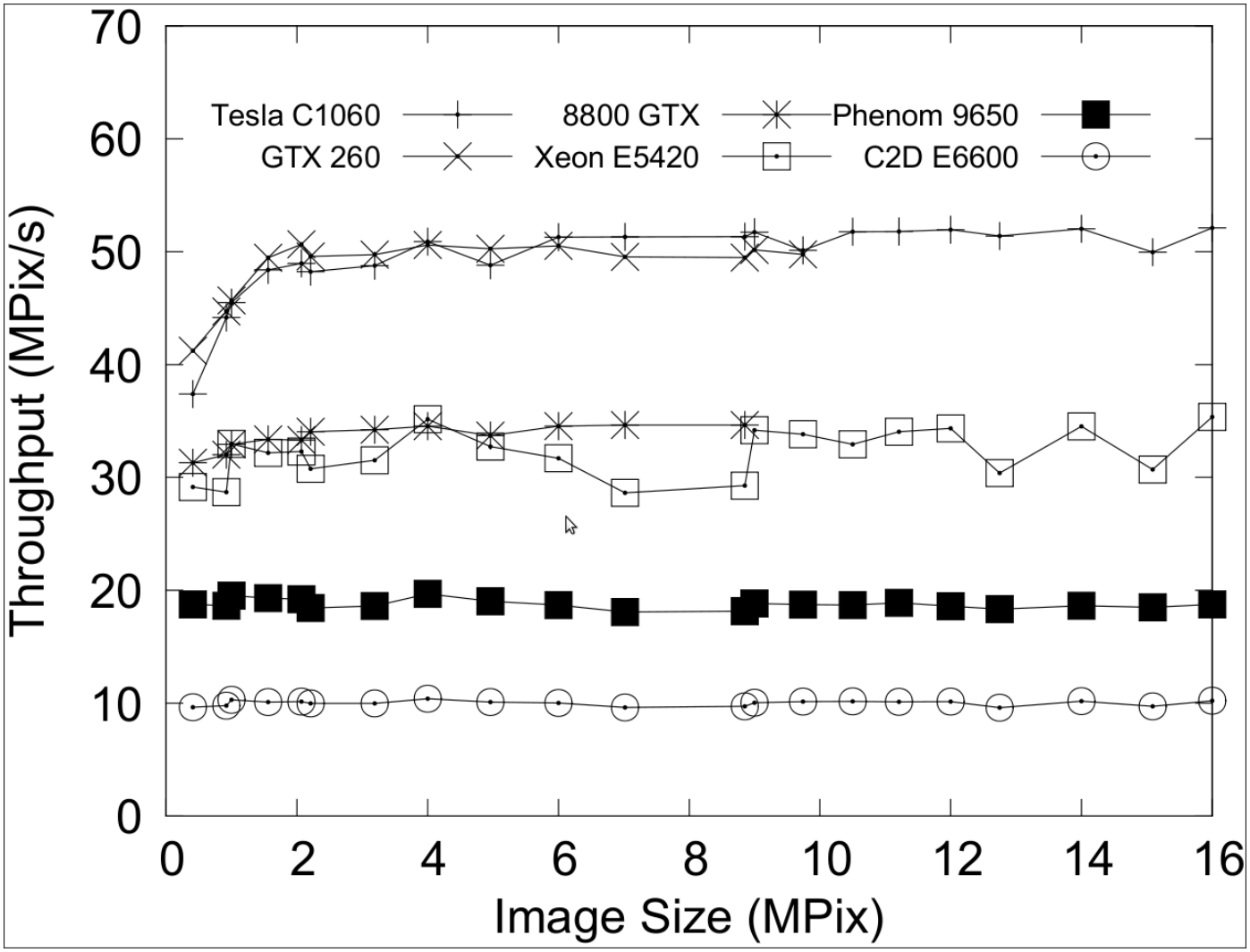
- **Memory access realignment.**
  - Additional requirement for **memory transaction grouping** in older hardware.
  - Thread 0, 16, 32, etc. must access a 16-element **aligned** region.
  - Images are appropriately aligned, but a **subregion** is probably not.
  - We can reassign the **thread:work mapping** to (mostly) fix this.

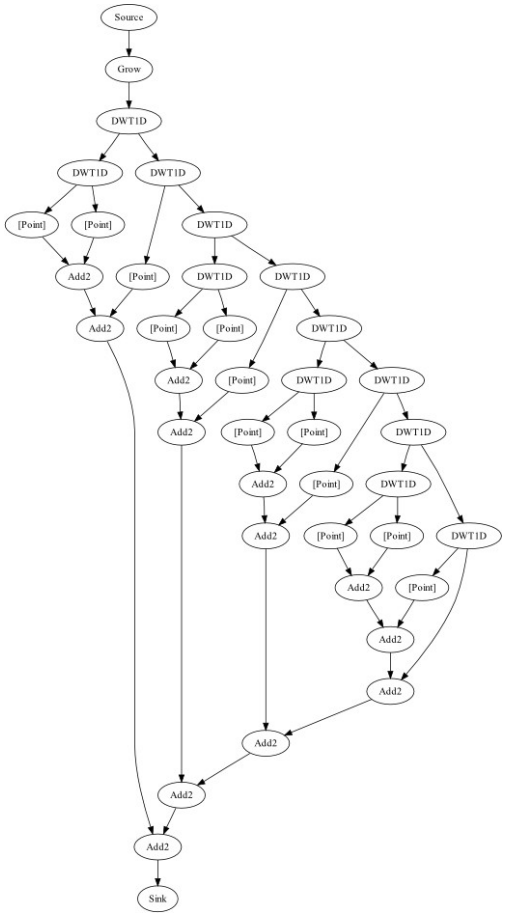


Performance Evaluation



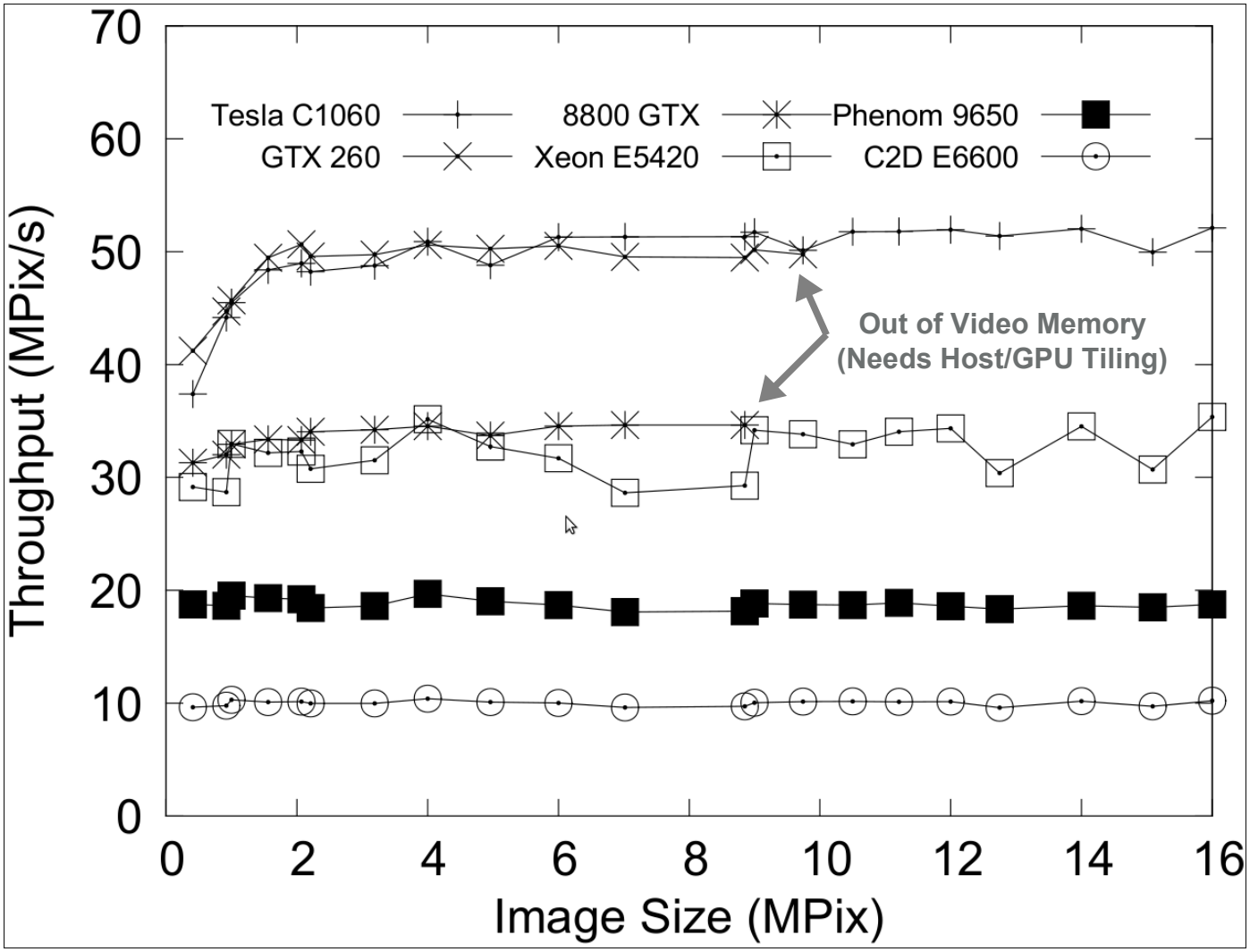
Performance Evaluation (Degraining)

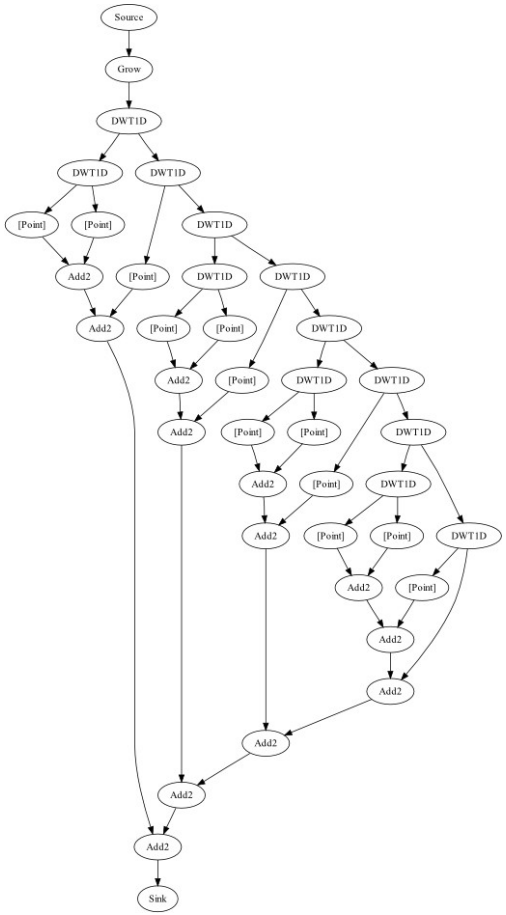




Wavelet-Based Degraining

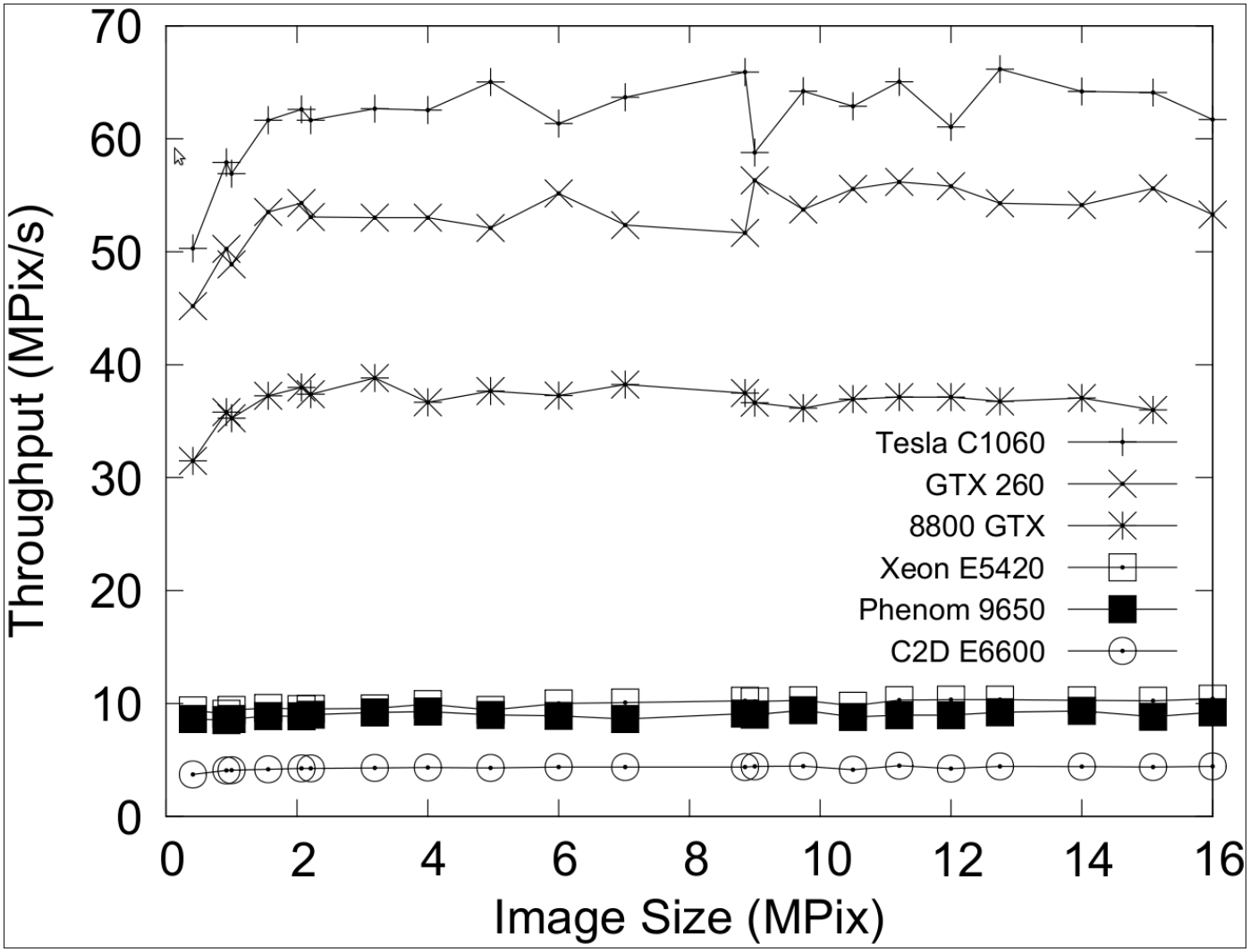
Performance Evaluation (Degraining)

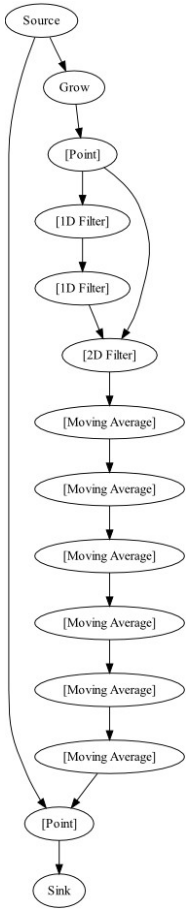




Wavelet-Based Degraining

Performance Evaluation (Diffusion Filtering)





Diffusion Filtering

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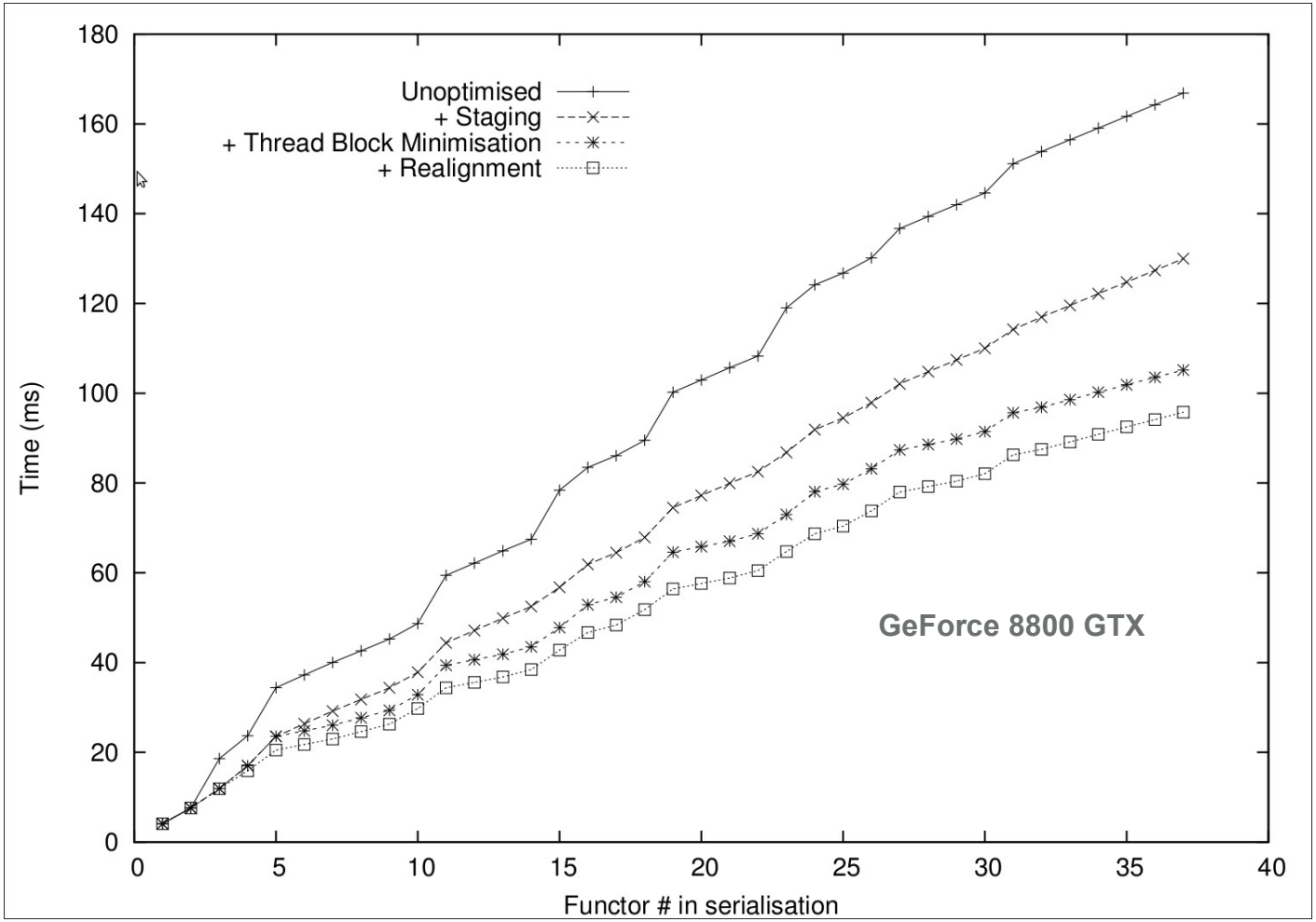
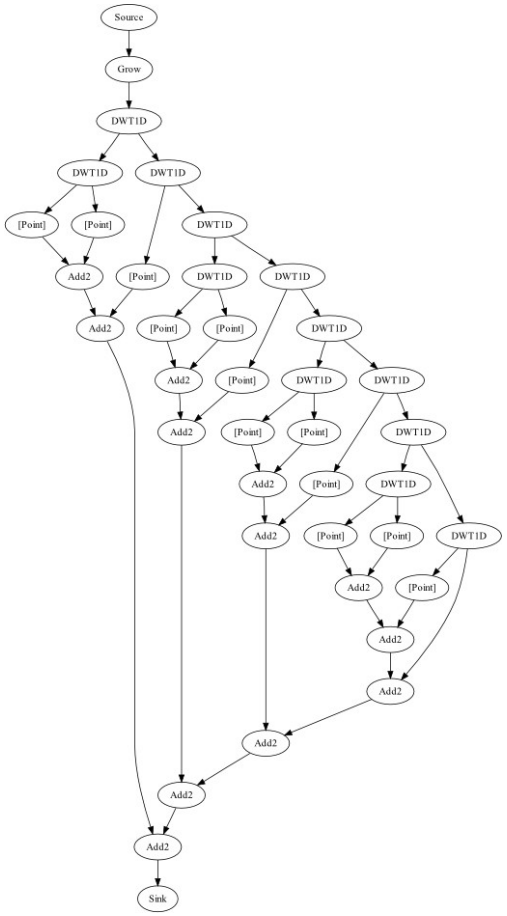
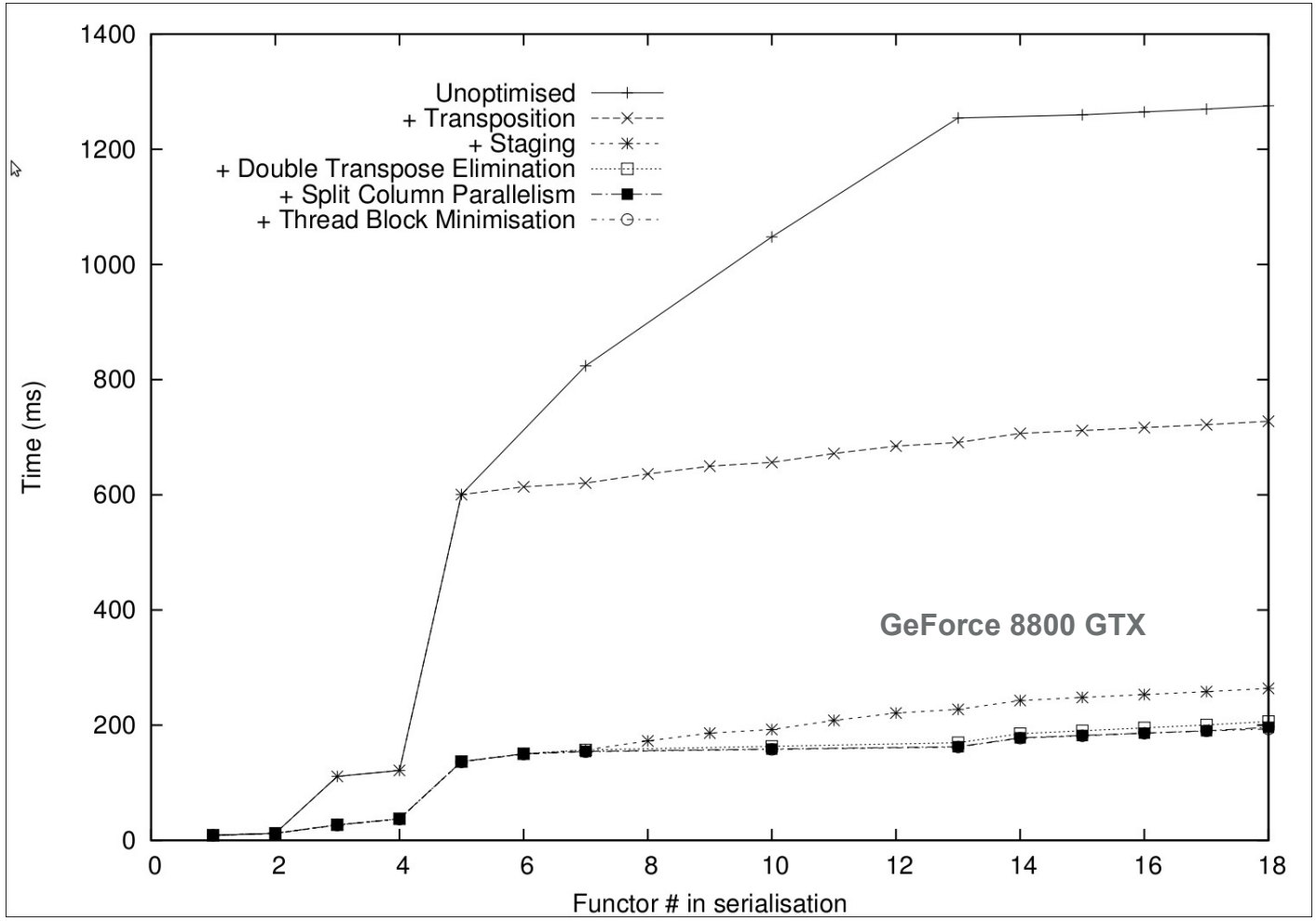
Performance Evaluation (Degraining)

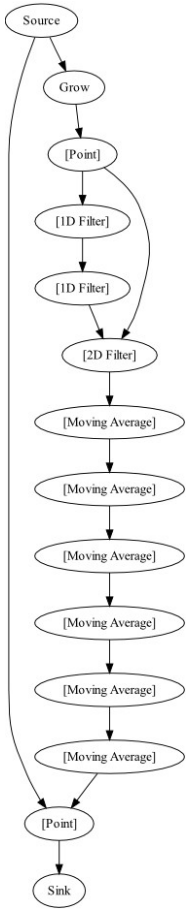




Wavelet-Based Degraining

Performance Evaluation (Diffusion Filtering)





Diffusion Filtering

Conclusions

- If performance requires parallelism and automatic optimisation:
  - Dependence information must be **built robustly into the code structure.**
  - Best effort parallelism cannot at present be relied upon.

- Metadata-supported frameworks **reduce** or **remove** the need for **code analysis**.
  - Trying to recover **high-level** algorithm concepts from an implementation is hard.
  - Many such concepts **embed** into the implementation **naturally**.
  - Source-to-source code generation allows **reuse** of **low-level** optimisations.

- Metadata are useful in a wide variety of optimisations.
  - In this presentation we outlined some optimisations for a **SIMT** architecture.
  - In previous work, we showed how metadata supports space and schedule optimisations to deliver large CPU speed-ups in visual effects DAGs.
  - In to-be-published work, we show how this framework supports **vectorisation** for SSE from the same source code (32 “cores”!).

Most importantly

- Metadata change the balance of development expertise.
  - High-performance software experts can work on the library framework.
  - Kernel authors can work on producing a kernel that generates the right result.
- Less developer time is used on platform-specific tuning.
- More time can be spent producing visual effects
  - Development effort targeted back to core values.
  - High performance still obtained.
- All of the work in this presentation is now moving from **prototype** to **production**.
  - Has been an opportunity to prototype our metadata and active libraries plans