Optimization of Tele-Immersion Codes

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Agenda

- 1. High-level goals
- 2. Tele-Immersion
- GPU specific optimizations applied
- 4. Results of the optimization effort
- 5. Future work
- 6. Conclusion



Main Goals

- Find data-parallel primitives and apply tuning techniques
 - Adapts for portability across multiple target architectures
 - E.g. Multi-cores, Clusters, and GPUs
 - Adapts for performance
 - E.g. optimal tile sizes, unroll factors, scheduling
 - Enables productivity
 - Programmer express data parallel operations
 - Focus more on their algorithms
- To do this study, we need good representative applications
 - Apply above to the domain of <u>Tele-immersion</u>



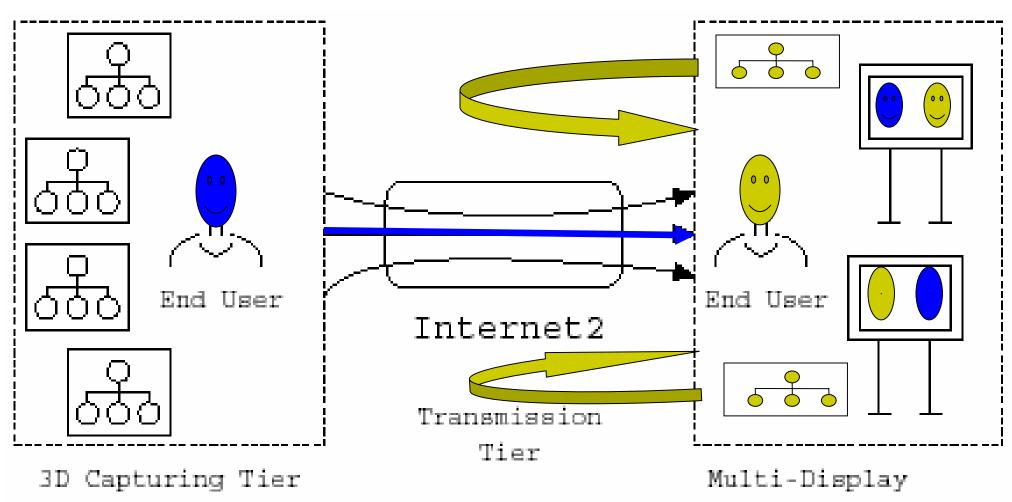
Tele-Immersion



Photo courtesy of Prof. Ruzena Bajcsy.

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Tele-Immersive Environment



Rendering/Displaying Tier



Initial Strategy

- Profile existing code to find hotspots
- Restructure original code as a sequence of data parallel operations
- Express these operations using new data structures
 - This enables targeting of multiple platforms
- Perform tuning on these newly restructured kernels



Overall Flow of TI Code

Main Thread						Post- processing	
Get Image Thread 0 (BW)							
Get Image Thread 1 (BW)	Pre-						
Get Image Thread 2 (BW)	processing						
Get Image Thread 3 (Color)							
Compute Thread 0		Triangulation			70 €		
Compute Thread 1		MNCC		Homogen	constru		
****				Homogen	Reconstruct Depth		
Compute Thread N					÷		
Time (ms):	12.1	12.0	5.5	17.8	2	1.8	Total: 51.2



Compute MNCC

- MNCC = Modified Normalized Cross Correlation
 - Computes correlation of feature points across different images
- Consists of two (consecutive) data parallel operations
 - Computation of correlation values
 - Maximum reduction
- Very little control flow (outside of maximum reduction)
 - Good candidate for GPUs



High-Level View of MNCC

Original Code

Restructured Code

```
compute_mncc (data , Thread ID) {
  int start = start edge for ID
  int end = end edge for ID
  for i=start, end {
    x1=x_edge[i];
    y1= y_edge [i];
    for j=0, num_disp {
       // find corresponding edges in L and R cameras
      x1 eL = (float *)(C2LX + x1* num disp);
       y1 eL = (float *)(C2LY + y1* num disp);
      maxcorr(i) = 0:
      for j=0, NUM DISP {
              corr1 = ...; corr2 = ....; corr3 = ....;
              // find maximum correlation
              corr [i* num_disp +j]= corr1 + corr2 + corr3;
              if (corr [i* num_disp +j]> maxcorr [i]) then
                 maxcorr [i] = corr [i* num disp +i];
```

```
compute mncc (data, Thread ID) {
  int start = start edge for ID
  int end = end edge for ID
  for i=start, end {
      for j=0, NUM_DISP {
       x1=x_edge[i];
       y1=y \text{ edge [i]};
       // find corresponding edges in L and R cameras
       x1 eL = (float *)& C2LX [x1* num disp];
       y1_eL = ( float *)& C2LY [y1* num_disp ];
       corr1 = ...; corr2 = ...; corr3 =...;
       corr [i* num disp +j]= corr1 + corr2 + corr3;
find maximum (data, Thread ID) {
  int start = start edge for ID
  int end = end edge for ID
  for i = start , end {
    maxcorr [i] =0;
     for j = 0, NUM DISP {
        if (corr [i* num disp +j]> maxcorr [i])
           maxcorr [i] = corr [i* num disp +j];
```

MNCC Optimizations (GPU)

1. Start with naïve (restructured) data parallel operation

- Easy port of the code to use CUDA
- Only outer loop is parallelized
- Empirically search for best thread block size

2. Introduce multiple dimensions of parallelism

- No dependences across loops
- Empirically search for best 2D thread block size

3. Transpose the thread block structure (Loop Interchange)

- Take advantage of memory coalescing
- Empirically search the best transposed 2D thread block size

4. Utilize texture memory as a hardware cache

Frequent 2D table lookups



Compute Homogen

- Data Parallel routine
- Apply similar restructuring techniques as in MNCC
- Lots of control flow
 - Consists of many divergent branches
 - Very input dependent
 - Potentially bad candidate for GPU
 - Good for CPUs using dynamic scheduling
 - Load imbalance
 - Overdecomposition will help here



Homogen Optimizations (GPU)

- 1. Start with naïve data parallel implementation
 - Same as MNCC
- 2. Utilize texture memory
 - Same as MNCC
- 3. Compiler flags
 - Nvcc compiler flag –maxregcount #
 - Beneficial impact on performance by forcing compiler to spill registers earlier



Initial Results

Test Platform 1:

- Intel 4-Core Penryn 2.83ghz
- 4GB memory/6MB L2 cache
- Nvidia GTX280 (Cuda 2.0)
- Intel ICC 10.1 Compiler/MS Visual C++

Test Platform 2:

- 4x6-Core Intel Dunnington Xeon 2.40ghz
- 48GB memory/12MB L3 cache
- Intel ICC 10.1

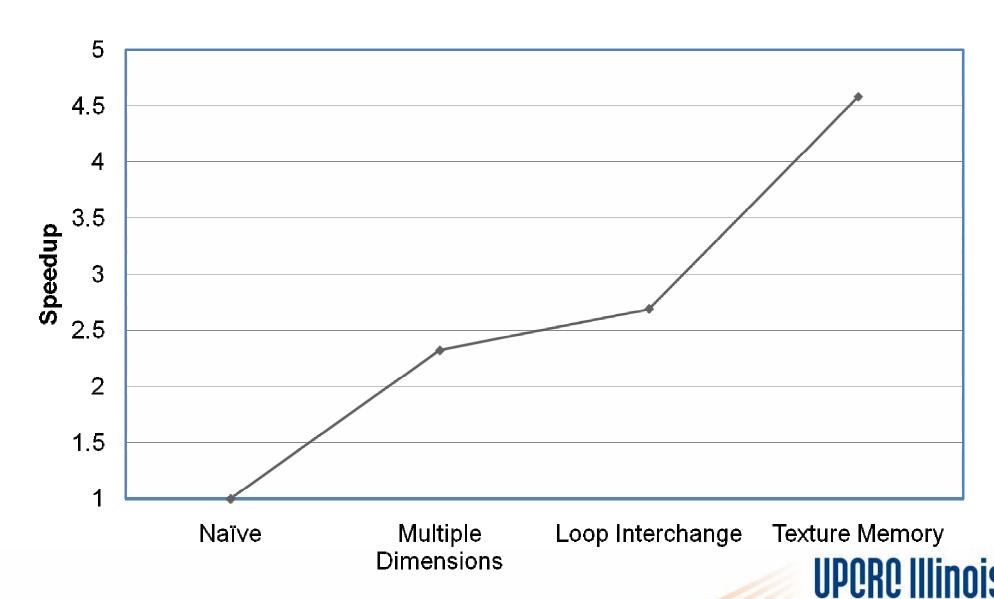


Compiler Results (4-Core Intel)

- Original Code
 - Microsoft Visual C++: 20fps
 - Intel ICC 10.1: 31fps
- Up to 35% speedup just from switching compilers
 - Mostly due to auto-vectorization

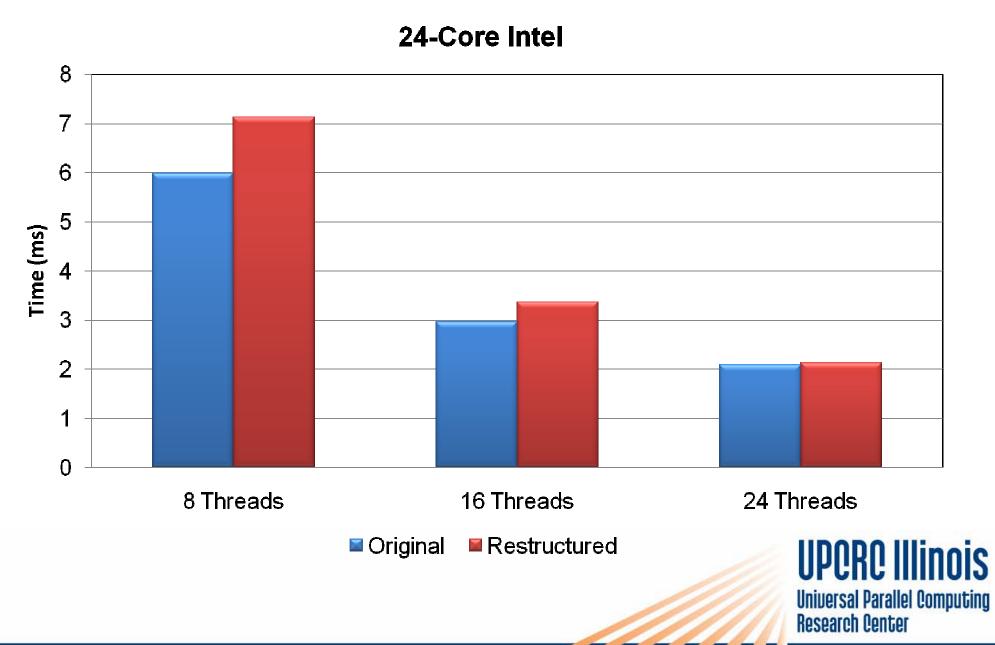


MNCC GPU Optimization Trend



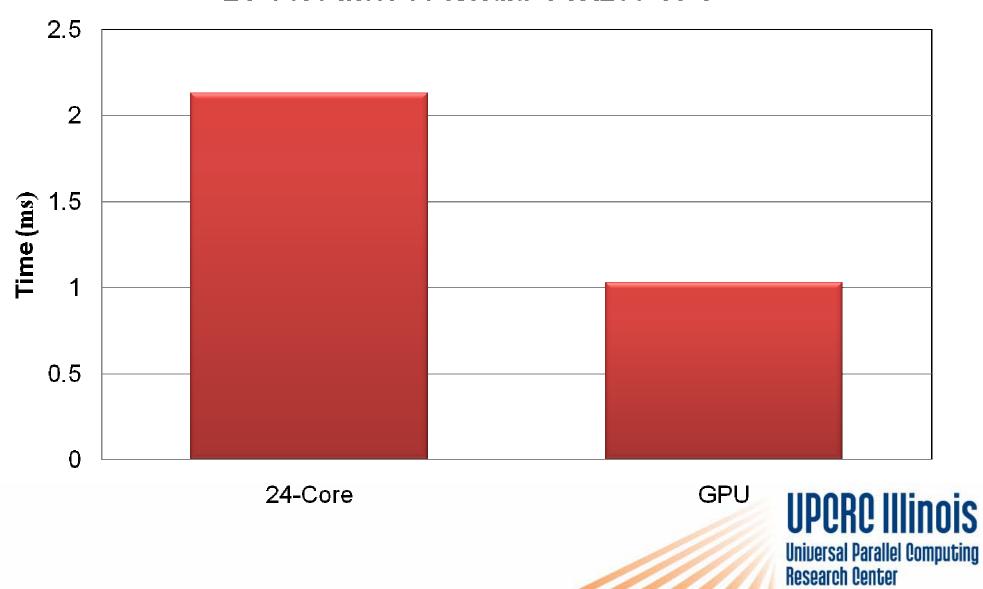
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MNCC Results (CPU)

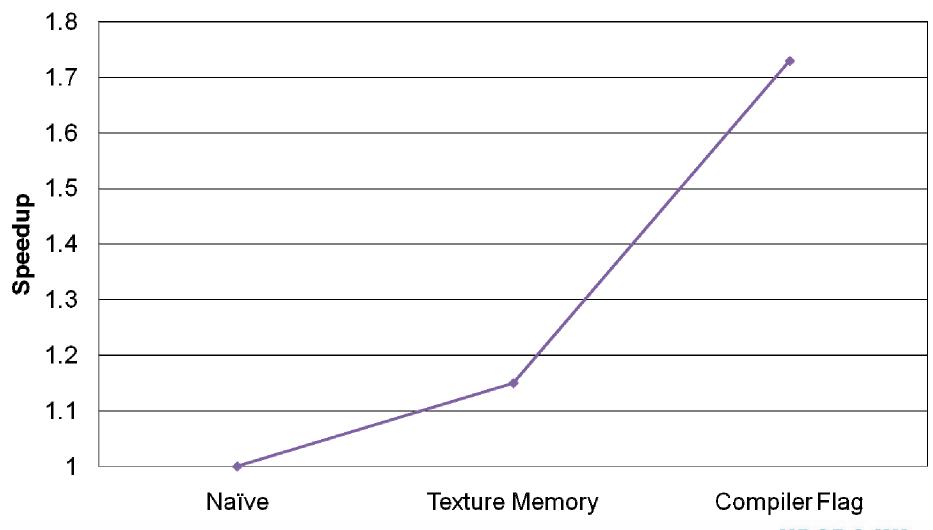


Optimized MNCC Results

24-Core Intel vs Nvidia GTX280 GPU

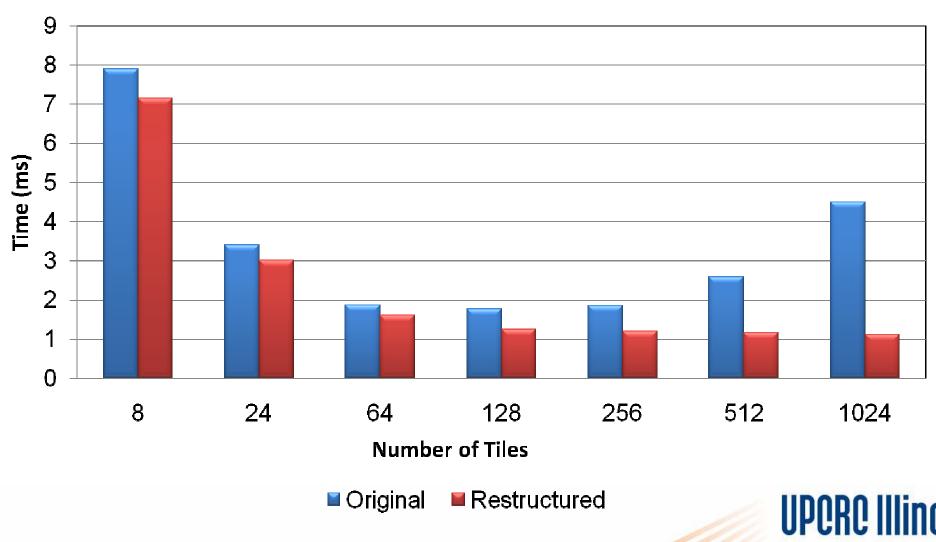


Homogen GPU Optimization Trend



Homogen Results (CPU)

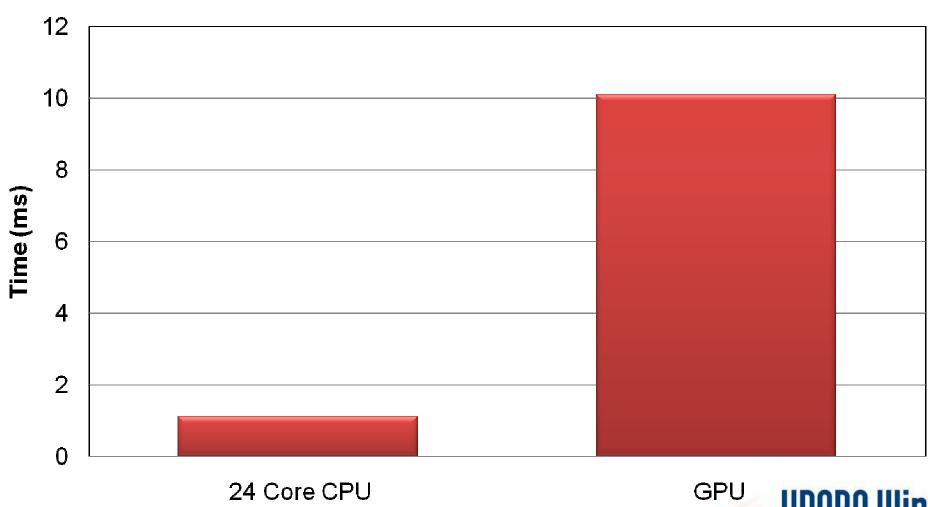






Optimized Homogen Results

24-Core Intel vs Nvidia GTX280 GPU





Overall Results (Modified)

Main Thread						Post- processing	
Get Image Thread 0 (BW)	Pre-processing						
Get Image Thread 1 (BW)							
Get Image Thread 2 (BW)							
Get Image Thread 3 (Color)							
Compute Thread 0		Т		Z.			
Compute Thread 1				Homogen	econstri		
		MNCC		uct Dep ogen	Reconstruct Depth		
Compute Thread N					#		
Time (ms):	12.1	1.03	6.4	1.12	0.5	1.8	Total: 22.95 (~44fps)



Work in progress

- Port kernels to use new data structures (HTAs)
 - HTA = Hierarchically Tiled Array
 - Facilitates locality and parallelism
 - Provides a "map" primitive
 - Performs a user-defined operation on an element-by-element or tile-by-tile granularity
 - Encapsulate parallelism from programmer
 - Target for multiple classes of parallel architectures
 - E.g. multi-cores, clusters, GPUs
- Add GPU backend to HTAs



Work in progress (cont.)

- Investigation of parallelization of Delaunay triangulation
 - K. Pingali, et. al (Galois)
- Further GPU tuning of Homogen in progress
- Adding empirical auto-tuning framework
 - Tune for performance on multi-cores and GPUs
- Look at future architectures such as Intel's Larabee



Conclusions

- Good performance from restructuring and tuning the kernels
- Switching compilers leads to large performance improvements
- Good scalability
 - For both large multi-cores and GPU platforms
 - GPU implementation of MNCC is up to 2x faster than a 24-core
- New bottlenecks appear after original optimizations



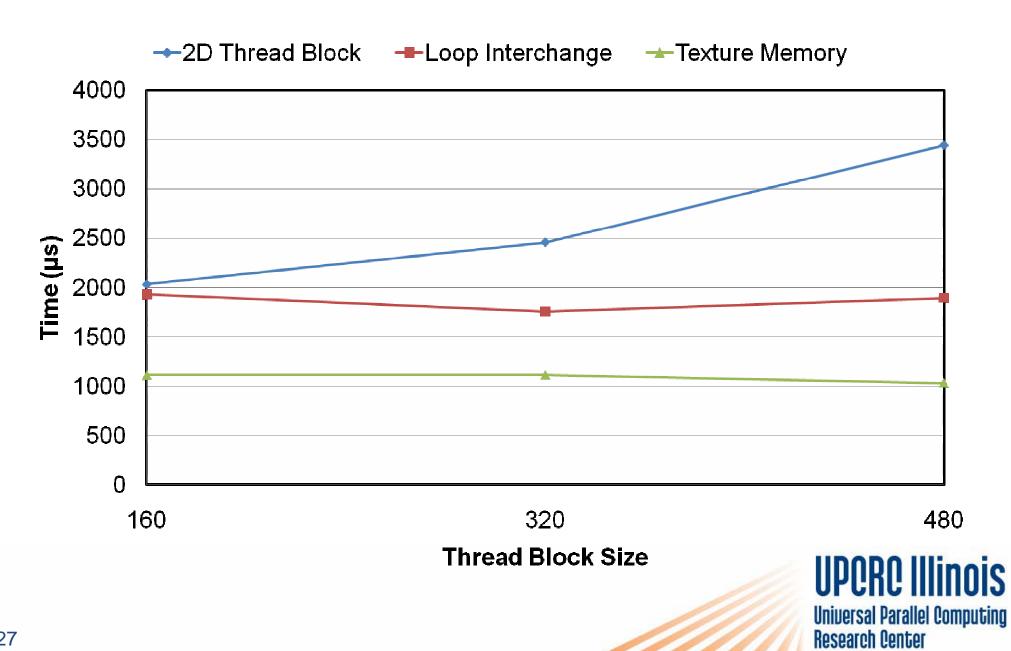
Questions?

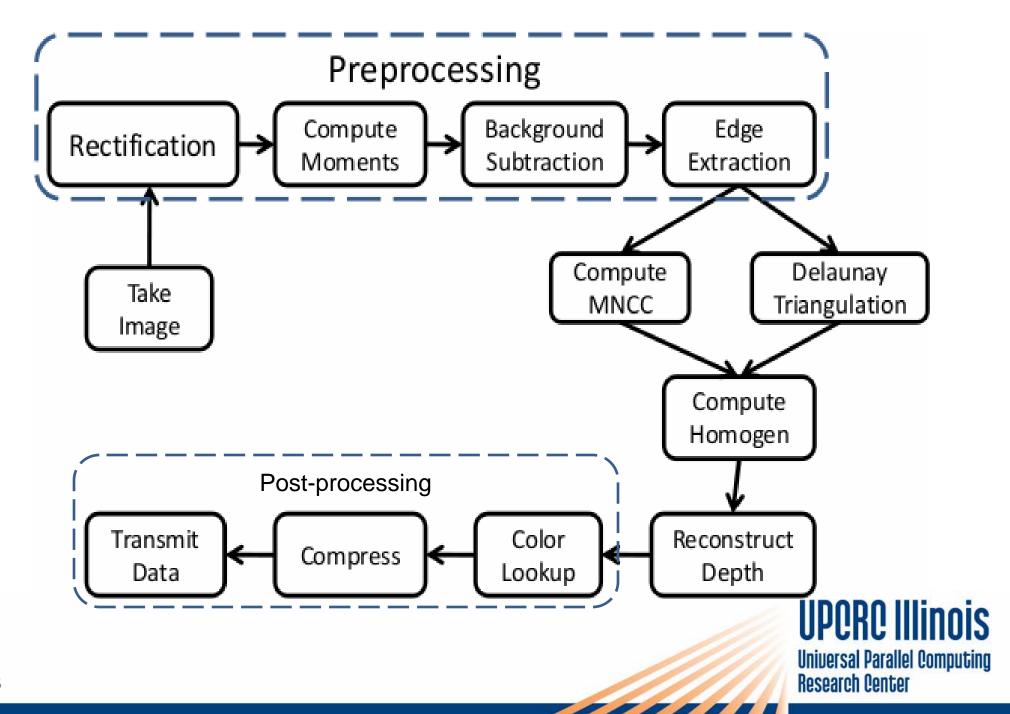


Backup Slides



Thread Block Size Impact on MNCC





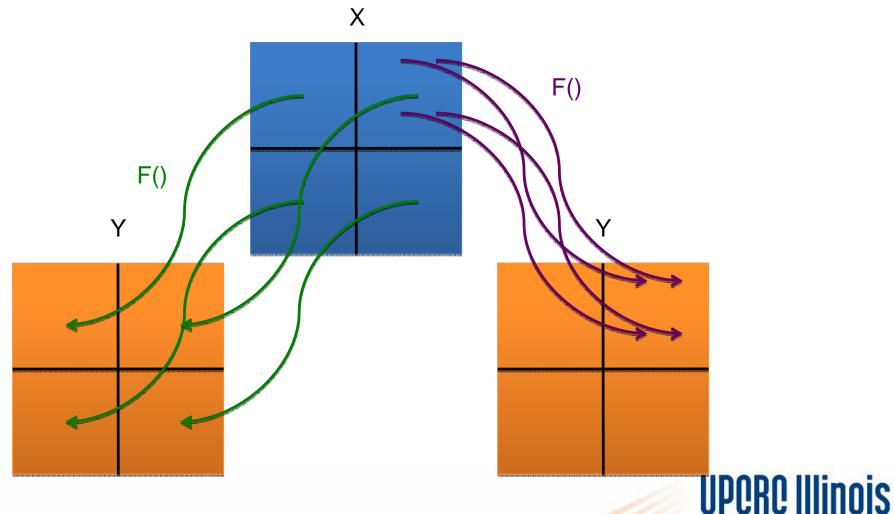
Compute Kernels

- MNCC and Homogen are the two most computationally expensive sections of code (~68% total execution)
 - MNCC → ~34% of total execution time
 - Compute Homogen → ~34% of total execution time
- Delaunay Triangulation is purely sequential
 - Parallel implementations exist (K. Pingali et. al)
 - Becomes bottleneck as MNCC is improved



User Defined Operations

hmap(F(), X, Y)



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Compute MNCC (cont.)

- We need to restructure original MNCC code
 - Allows for Hmap on element-by-element, or tile-by-tile
 - This can exploit more parallelism
 - Kernels are now simpler and easier to understand
 - Simpler code can possibly enable more compiler optimizations
- Perform traditional compiler optimizations on the kernels
 - Converting code to perfectly nested loops
 - Changing pointer arithmetic to array subscripts
 - Benefits readability, but might worsen performance
 - Loop fusion
 - Code movement
 - Dead code elimination



Compute MNCC Restructuring

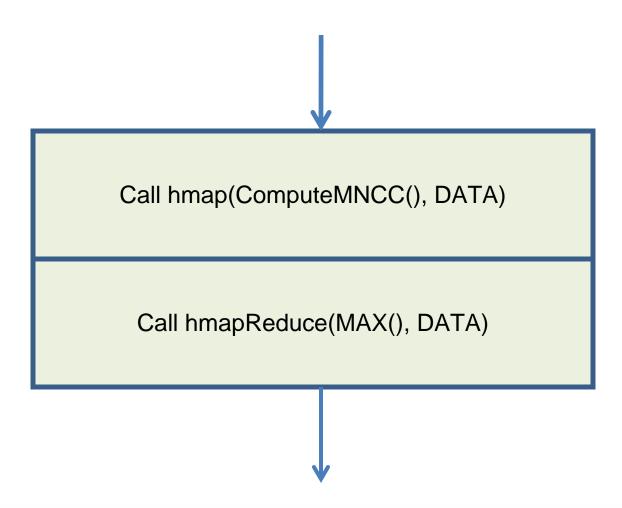
Original MNCC

```
compute_mncc(data, Thread ID) {
  int start = start of range for ID
  int end = end of range for ID
  for I = start, end
   ...
   for J = 0, NUM_DISP {
      ...
   }
   for J = 0, NUM_DISP {
      ...
      corr_vals(I * NUM_DISP + J) = ...
   }
  find maximum value and index
}
```

Restructured MNCC

```
compute mncc(data, Thread ID) {
     int start = start of range for ID
     int end = end of range for ID
     for I = start, end
        for J = 0, NUM DISP {
          corr vals(I * NUM DISP + J) = ...
find maximum(data, Thread ID) {
     int start = start of range for ID
     int end = end of range for ID
     for I = start, end
        for J = 0, NUM DISP {
        find maximum value and index
```

Hmap conversion



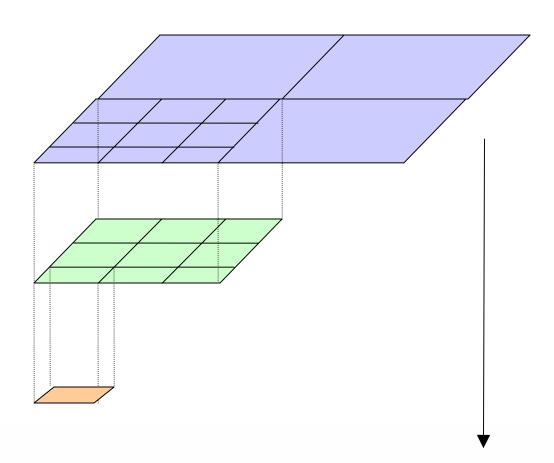


Overall Results (Original)

Main Thread						Post- processing	
Get Image Thread 0 (BW)	Pre- processing						
Get Image Thread 1 (BW)							
Get Image Thread 2 (BW)							
Get Image Thread 3 (Color)							
Compute Thread 0		Triangulation			Re		
Compute Thread 1		MNCC		Homogen	Reconstruct Depth		
Compute Thread 7					Ď		
Time (ms):	12.1	12.0	5.5	17.8	2	1.8	Total: 51.8 (~19.3fps)



HTA Data Structure



Distributed

Multicore

Locality

