Parallel Computing Class Homework Assignment Proposal

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Goals

Reasonable coverage of important parallel primitives and interesting image processing applications

Emphasis on empirical performance evaluation

Parallel primitives covered in this proposal

Map

Scatter/Gather

Stencil

Reduce

Scan

Segmented Scan

Compact

Sort

Image processing applications covered in this proposal

Color Conversion

Gaussian Blur

Bilateral Filtering

Red Eye Removal

Tonemapping

Poisson Blending

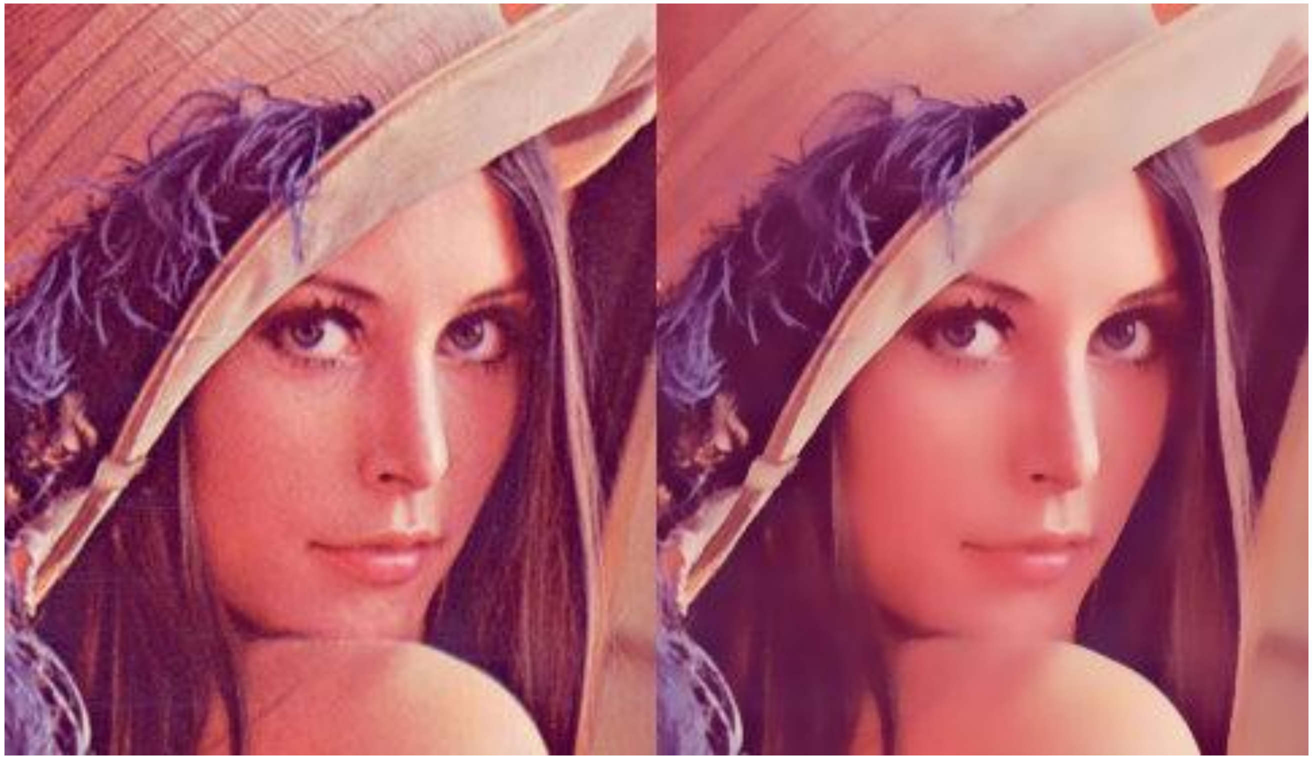
Graph Cuts

HW1: Greyscale Conversion

HW1: Greyscale Conversion

- Hello CUDA
- Convert color image to greyscale
- Parallel primitives covered:
  - Map
- Performance evaluation questions:
  - How does performance vary with block size?
  - How does performance vary with image size?
- Estimated difficulty: Easy

HW2: Gaussian Blur and Smart Blur using the Bilateral Filter



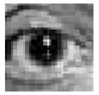
HW2: Gaussian Blur and Smart Blur using the Bilateral Filter

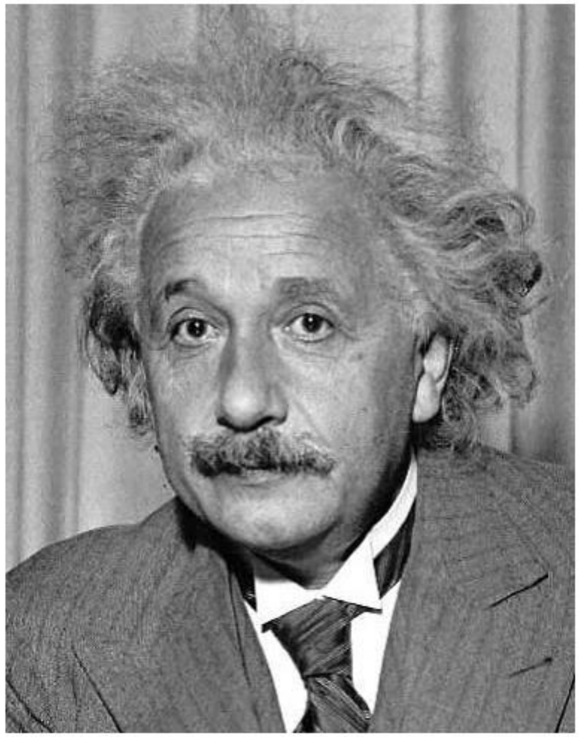
- Typical Guassian Blur using convolution
- Bilateral filter is just like Gaussian blur but with data-dependent kernel weights.
- See Joe Stam’s GTC 2009 talk, “Convolution Soup: A Case Study in CUDA Optimization” for possible optimizations
- Parallel primitives covered:
  - Map, Scatter/Gather, Stencil
- Performance evaluation questions:
  - What memory space to put blur kernel?
  - How does performance vary with kernel size?
  - Can we put the image to be blurred in texture memory?
  - How does performance vary with image size?
- Estimated difficulty: Moderate

HW2: Gaussian Blur and Smart Blur using the Bilateral Filter

- Decided against anisotropic diffusion for implementing smart blur
  - Although anisotropic diffusion can produce comparable results to bilateral filtering, it is less common in the literature
  - Anisotropic diffusion also has more parameters to tune and requires iteratively solving a partial differential equation over the image domain
  - In contrast, bilateral filtering has fewer parameters to tune and requires only one pass over the image.
  - Therefore, I think it is more useful to expose students to bilateral filtering

HW3: Automatic Red Eye Removal Using Template Matching (optional – we might want to replace this one)

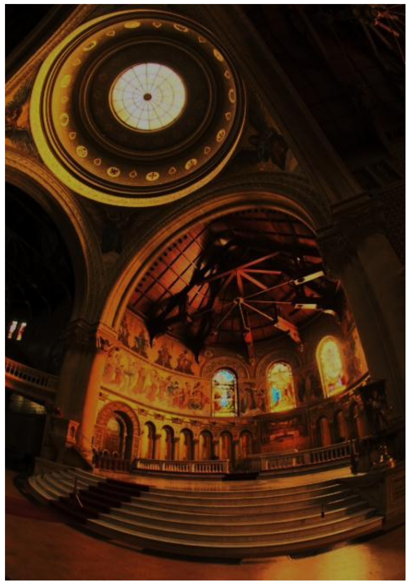
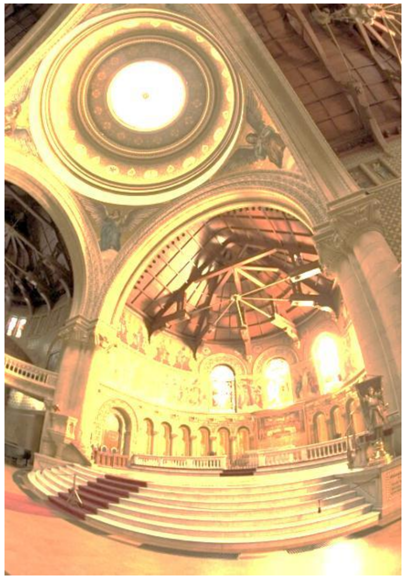
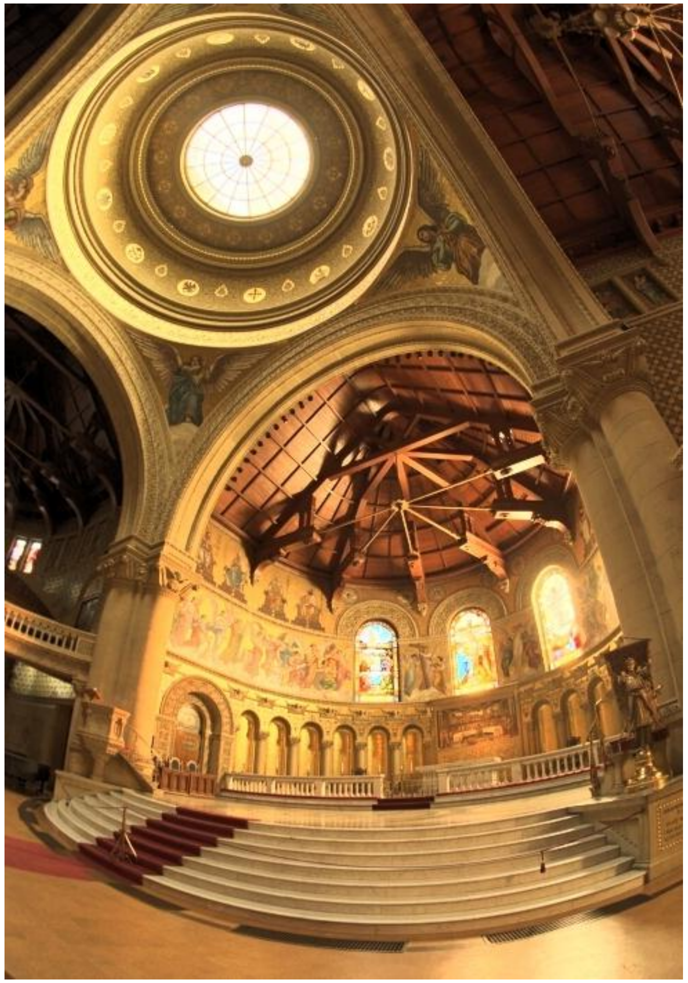
- Goal: find  in image



HW3: Automatic Red Eye Removal Using Template Matching (optional – we might want to replace this one)

- Convolve *original image* with an *eye template* to produce a *response image*
- Eye pixels will be the brightest pixels in the *response image*
- Sort pixels in the *response image* according to brightness to get all the eye pixels in the *original image*
- Reduce the redness of eye pixels
- See http://www.cs.illinois.edu/class/sp11/cs543/ (Lecture 7) for details
- Use experience from previous assignment, convolution should be easy, students can focus on sorting
- Best image processing application I could think of that relies directly on sorting
- Parallel primitives covered:
  - Map, Scatter/Gather, Stencil, Sort
- Performance evaluation questions:
  - Similar to previous assignment, but also how can we implement sort efficiently?
  - Lots of options for implementing an efficient sort
- Estimated difficulty: Moderate

HW4: High Dynamic Range Tone Mapping using Ward's Histogram Adjustment Operator

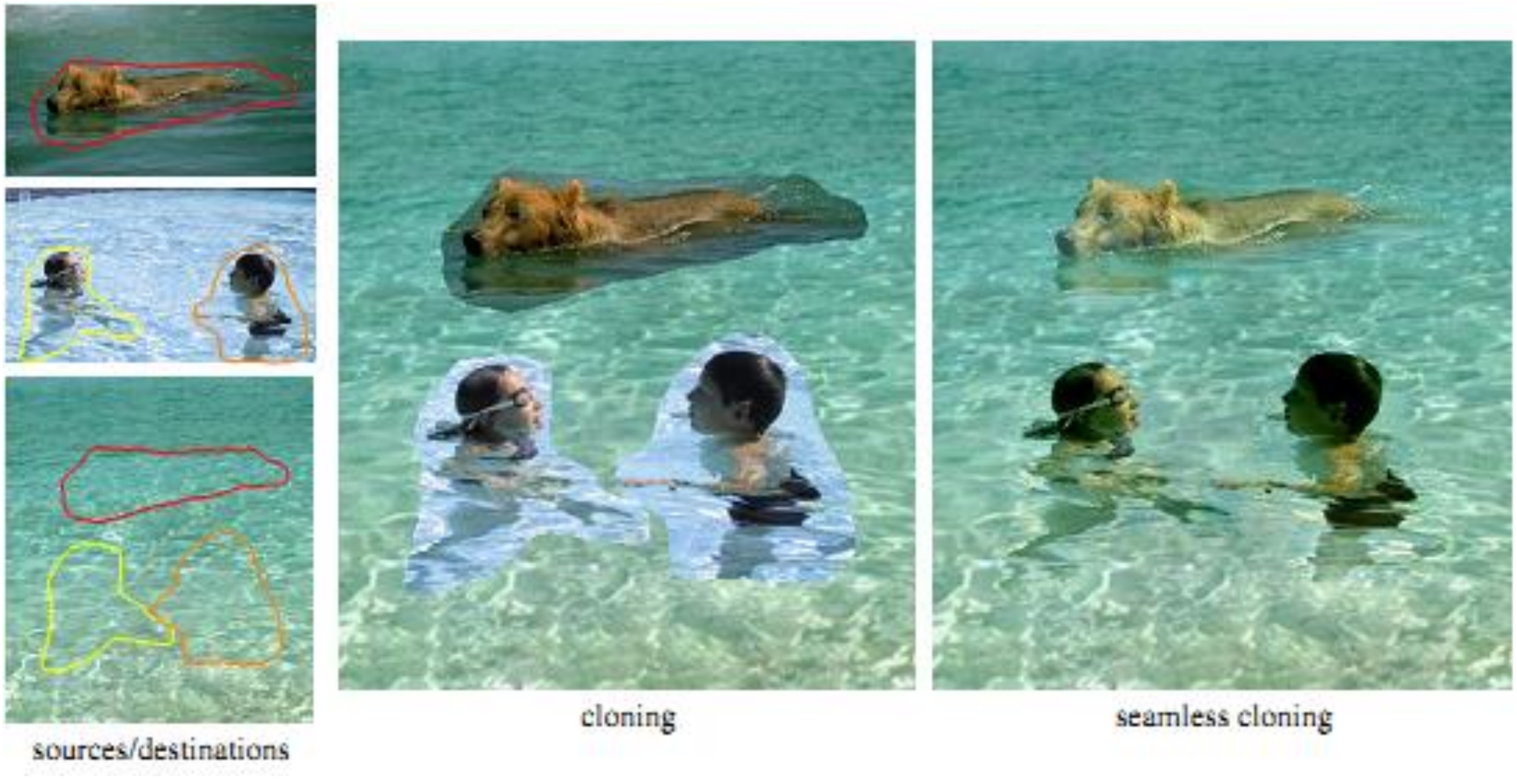
HW4: High Dynamic Range Tone Mapping using Ward's Histogram Adjustment Operator

- Compute global minimum and maximum luminance for image (reduce)
- Compute luminance histogram for image (scatter/gather using atomic operations)
- Adjust histogram using Ward's algorithm (iterated map and reduce)
- Compute the cumulative distribution function for the histogram by prefix-summing the histogram (scan)
- Use the cumulative distribution function as the luminance remapping curve (map)
- Parallel primitives covered:
  - Map, Scatter/Gather, Reduce, Scan
- See original paper and followup GPU paper for details:
  - http://radsite.lbl.gov/radiance/papers/lbnl39882/tonemap.pdf
  - http://developer.amd.com/gpu_assets/GPUHistogramGeneration_I3D07.pdf
- Similar homework assignment in MIT Computational Photography course
- Decided against Reinhart-style histogram equalization (SIGGRAPH 2002) because it seemed more complicated and less amenable to parallelization
- Estimated Difficulty: Moderate

HW5: Implementing Different Histogram Algorithms and Evaluating Their Performance

- Implement improved histogram algorithms for the previous assignment and evaluate the relative performance of each:
  - Sort the input, bin the sorted input, perform segmented prefix sum to accumulate the number of values in each bin, compact to compute histogram
  - Use shared memory where possible, use a hierarchical decomposition strategy where number of bins exceeds size of shared memory
- See the following papers for details:
  - http://developer.amd.com/gpu_assets/GPUHistogramGeneration_I3D07.pdf
  - http://developer.download.nvidia.com/compute/cuda/1.1-Beta/x86_website/projects/histogram64/doc/histogram.pdf
  - http://parse.ele.tue.nl/system/attachments/10/original/GPGPU_High%20Performance%20Predictable%20Histogramming%20on%20GPUs.pdf
  - http://innovativeparallel.org/Presentations/INPAR%20Modestly%20Faster%20GPU%20Histograms%20PDF.PDF
- Parallel primitives covered:
  - Map, Scatter/Gather, Segmented Scan, Compact, Sort
- If students are required to implement sorting in this assignment, then we might want to replace HW3 with HW8
- Quite open-ended. We could make this into a contest to see who can get the best performance.
- Estimated Difficulty: Hard

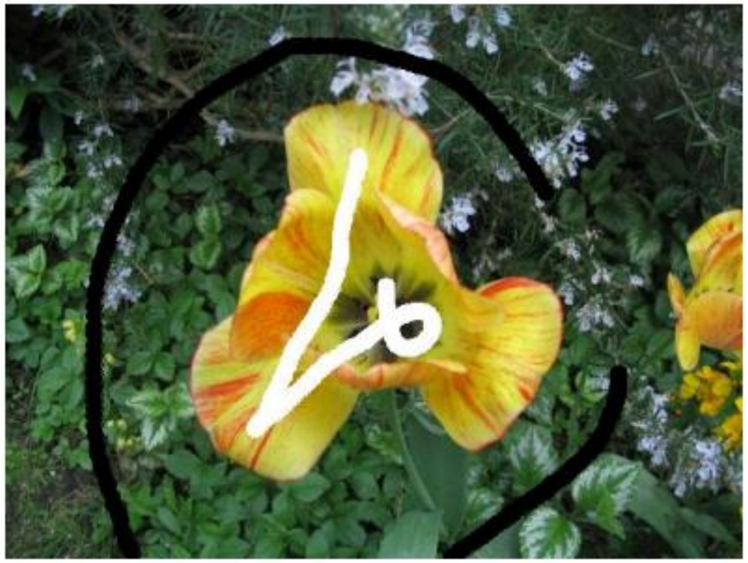
HW6: Seamless Image Compositing using Poisson Blending

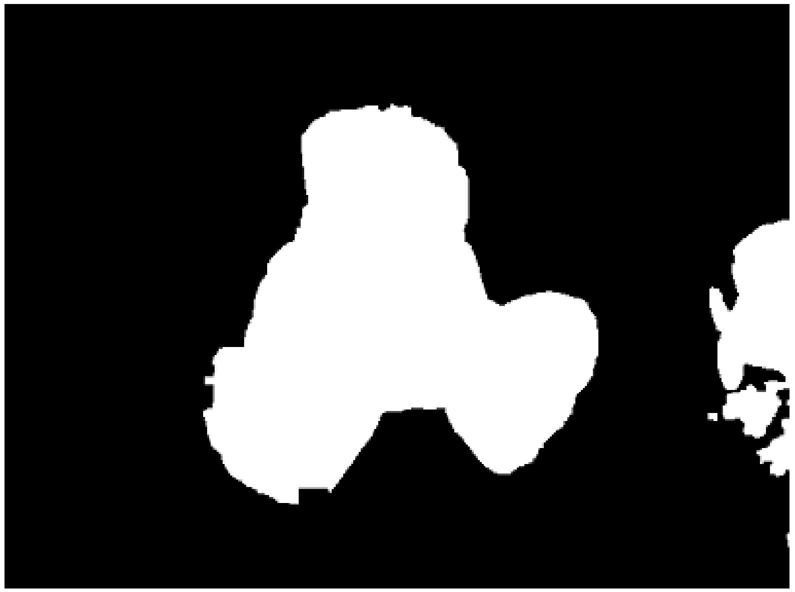


HW6: Seamless Image Compositing using Poisson Blending

- Given a *source image* and a *target image*, compute an *output image*
- The *output image* must respect a system of linear equations that relates the *gradients* of the *source image*, the *intensities* of the *target image*, and the *intensities* of the *output* image
- Construct a system of linear equations and solve using the Jacobi Method
- See the following papers for details on Poisson Blending:
  - http://www.cs.brown.edu/courses/csci1950-g/asgn/proj2/resources/PoissonImageEditing.pdf
  - http://www.cs.jhu.edu/~misha/Fall07/Notes/Perez.pdf
  - http://www.cs.jhu.edu/~misha/ReadingSeminar/Papers/Jeschke09b.pdf
- See the following paper for details on solving the Poisson equation using the Jacobi Method:
  - http://http.developer.nvidia.com/GPUGems/gpugems_ch38.html
- Parallel primitives covered:
  - Map, Scatter/Gather, Stencil, Reduce
- Performance evaluation questions:
  - Can we use shared memory to solve the Poisson equation more efficiently?
  - Are there other numerical methods that we can use to solve the Poisson equation more efficiently?
  - What are the convergence properties of these methods?
- Similar homework assignment in Brown, UIUC, and MIT Computational Photography courses, CMU Advanced Parallel Graphics course
- Estimated difficulty: Hard

HW7: Selecting Irregular Image Regions using Graph Cuts


Input


Result

HW7: Selecting Irregular Image Regions using Graph Cuts

- Set up a weighted undirected graph of nodes (pixels) and edges (connecting neighboring pixels)
- Set edge weights according to gradient magnitudes in the image
- Execute the push-relabel algorithm on each node in parallel until all nodes converged
  - Naïve implementation requires global atomic operations
- See Timo Stich's GTC 2009 talk, "Graph Cuts with CUDA" for more details
- Parallel primitives covered:
  - Map, Scatter/Gather, Stencil, Reduce
- Similar homework assignment in UIUC Computer Vision course, Brown and MIT Computational Photography courses, CMU Advanced Parallel Graphics course
- Estimated difficulty: Hard

HW8: Improving the Performance of Push-Relabel (optional – we need to remove HW3 and replace it with this)

- Use shared memory, change degree of parallelism to avoid global atomic operations
- Keep list of active image tiles using stream compaction
- See the following papers for details:
  - http://cvit.iiit.ac.in/papers/rtGCuts_2008.pdf
  - http://people.seas.harvard.edu/~mroberts/data/a_work-efficient_gpu_algorithm_for_level_set_segmentation_hpg_paper.pdf
- Parallel primitives covered:
  - Map, Scatter/Gather, Stencil, Reduce, Scan, Compact
- Quite open-ended. We could make this into a contest to see who can get the best performance
- Estimated difficulty: Hard

Summary

Topics	HW1: Conversion from Color to Greyscale	HW2: Gaussian Blur and Smart Blur using the Bilateral Filter	HW3: Automatic Red Eye Removal using Template Matching	HW4: High Dynamic Range Tonemapping using Ward's Histogram Adjustment Algorithm	HW5: Implementing Different Histogram Algorithms and Evaluating their Performance	HW6: Seamless Image Compositing using Poisson Blending	HW7: Selecting Irregular Image Regions using Graph Cuts	HW8: Improving the Performance of Push-Relabel
Primitives								
Map	X	X	X	X		X	X	X
Scatter/Gather		X	X	X	X	X	X	X
Stencil		X	X			X	X	X
Reduce				X		X	X	X
Scan				X	X			X
Segmented Scan					X			
Compact					X			X
Sort			X		X			

Notes

- Decided against "swishy picture" effect driven by a Stable Fluids simulation
  - This kind of effect is certainly important, but I feel that the other homework assignments represent image processing operations of broader interest
  - The most interesting part of most fluid simulations (from parallel programming perspective) is solving the Poisson equation to enforce incompressibility, thereby enforcing global constraints on the fluid
  - We are covering this pattern in the Poisson Blending assignment

Notes

- Decided against fisheye warp effect
  - This kind of warping is certainly important, but I feel that the other homework assignments represent image processing operations of broader interest
- Decided against seam carving
  - In some sense, the graph cuts assignment is a generalization of seam carving
  - It seems challenging to expose enough parallelism in the seam carving dynamic programming algorithm
    - If carving vertically, can only process one row at a time
    - If carving horizontally, can only process one column at a time
    - Only 1024 threads of independent work to do for a 1024 X 1024 image