MIC-GPU: High-Performance Computing for Medical Imaging on Programmable Graphics Hardware (GPUs)

SPIE Medical Imaging

Code Optimization Case Study and Demo

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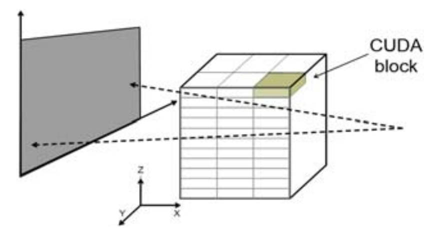
Optimization Case Study

Goal:
- test various optimization strategies and tweak to maximize impact
- using Filtered Backprojection for this case study

Optimization #1: minimize shared memory usage
- update a block of voxels per thread (optimum was 16 × 16 × 4)
- orientation-neutral block minimizes “shadow” on projections



Optimization Case Study

Optimization #2: exploit special GPU (ASIC) hardware
- we store projection data in texture memory
- allows fast bilinear interpolation
- frees up registers without penalty since texture is cached

Optimization #3: exploit constant memory
- we store projection (system) matrix in constant memory
- frees up shared memory and reduces global memory accesses

Optimization #4: increase thread granularity
- backproject multiple projections in one thread (optimum was 4)
- reduces global memory accesses and number of kernel invocations

Optimization Case Study

Optimization #5: Pre-fetching
- pre-fetch data while computing on previous data
- incurs some shared memory overhead but worked out OK

Optimization #6: Page-locked memory
- page-lock the result array
- forces OS to store this data on one contiguous page of memory
- eliminates the need for page swaps

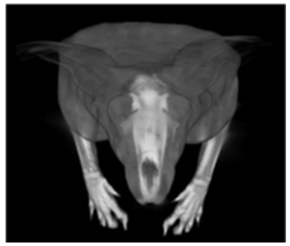
Other optimization strategies: loop unrolling, fast math
- we tried these but they did not yield much benefits in this specific case

Case Study – Rabbit CT

Benchmarking framework:
- developed by Rohkohl et al.
- FDK backprojection algorithm
- 496 projections of a rabbit
- 1,248 X 960 pixels each

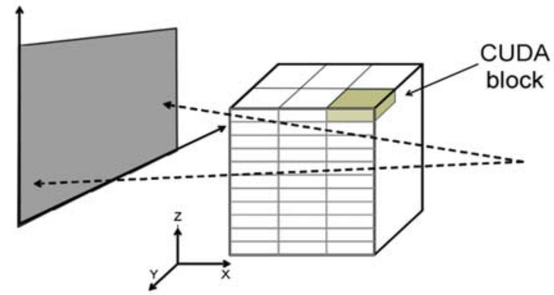
Advantages:
- enables true comparisons
- embeds the system matrix already
- 'just' accelerate the backprojection
- measures timings
- measures reconstruction errors

Leaderboard
- benchmark new code
- 256^3, 512^3, 1024^3 volume reconstructions



Setup

Approach:
- each thread computes an array of voxels



Thread Block Dimension: 16 x 16 x 4

Winning Implementation #1

```
texture<float, 2> tRef, tRef2, tRef3, tRef4
__constant__ float A[48]

row = blockIdx.y * blockDim.y + threadIdx.y
col = blockIdx.x * blockDim.x + threadIdx.x
FOR k = 0 to L
  result = f_L[k * L² + row * L + col]
          . . .
  // mapping voxel (x,y,z) to projection 1 and backproject
  w = A[2] * x + A[5] * y + A[8] * z + A[11]
  u = (A[0] * x + A[3] * y + A[6] * z +A[9]) / w
  v = (A[1] * x + A[4] * y + A[7] * z + A[10]) / w
  result += tex2D ( tRef, (u + 0.5), (v + 0.5)) / w²

  //repeat for projection 2 with A[12-23] and tRef2
  //repeat for projection 3 with A[24-35] and tRef3
  // repeat for projection 4 with A[36-47] and tRef4

  f_L[k * L² + row * L + col] = result
END
```

+ page-lock memory
+ pre-fetch data

E. Papenhausen, Z. Zheng, K. Mueller, "GPU-Accelerated Back-Projection Revisited: Squeezing Performance by Careful Tuning,"

Winning Implementation #2

RapidRabbit strikes back
- re-order projection and voxel loop (improves locality)
- faster perspective divide and depth weighting using fast inverse square root

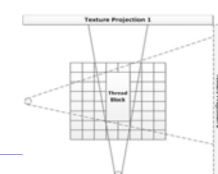
  $w = a_2x + a_5y + a_8z + a_{11}$

  $w' = rsqrt(w * w)$

  $u = (a_0x + a_3y + a_6z + a_9) * w'$

  $v = (a_1x + a_4y + a_7z + a_{10}) * w'$

  $result \mathrel{+}= tex2D(tRef, (u+0.5), (v+0.5)) * w' * w'$
- accumulation via atomic adds
- staged page-locks
- transpose volume at 45°



E. Papenhausen, Z. Zheng, K. Mueller, "Rapid Rabbit: Highly Optimized GPU Accelerated Cone-Beam CT Reconstruction," IEEE Medical Imaging Conference,

SPIE Medical Imaging 2016

Demo

handing over to Sungsoo