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Real-Time Semi-Global Matching Disparity Estimation on the GPU

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Motivation

- Stereo Matching is a frequently required task
- Applications
 - Driver Assistance Systems
 - 3D image processing for real-time feedback
 - Keyhole surgery
 - Subtitle placement
- Implementation on off-the-shelf devices for low-cost availability in desktop computing systems: GPUs

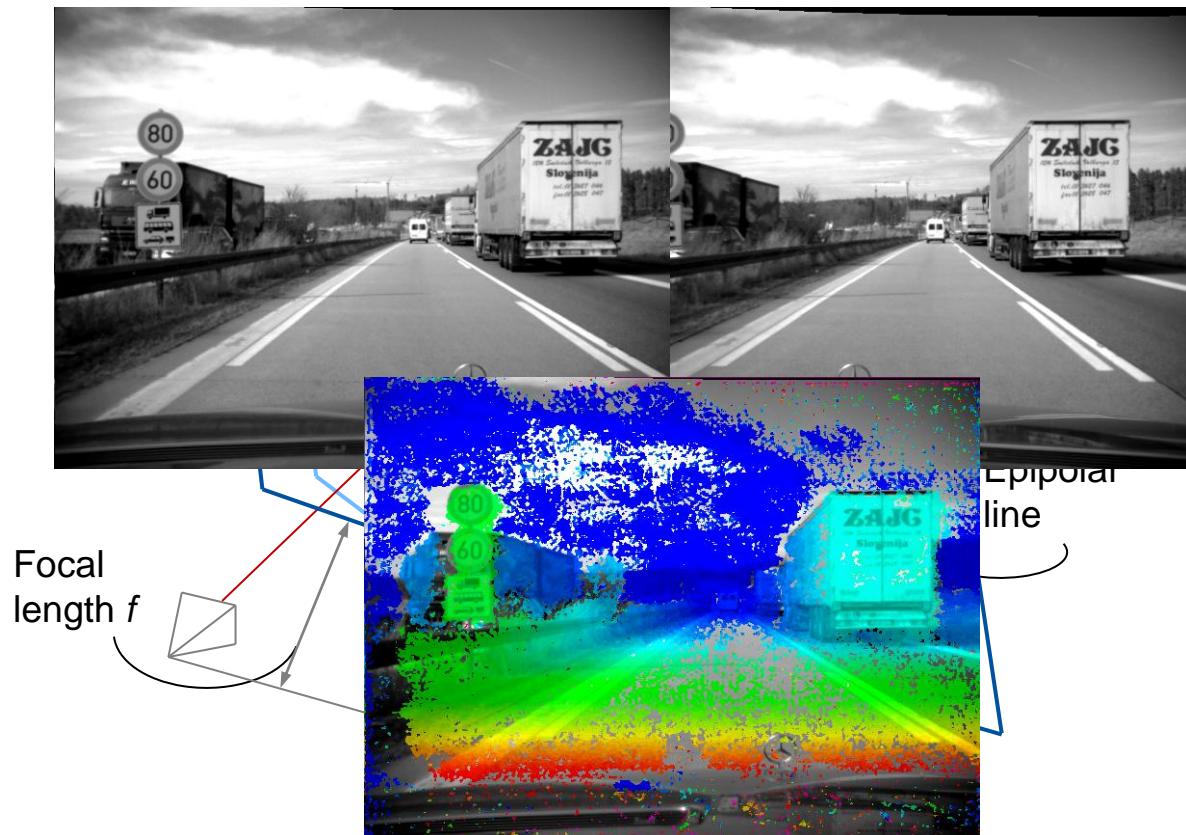
Estimation

Identifying the projection point of a 3-D real-world point in two or more images taken from distinct viewpoints

Existing implementations :

GPU [Gibson '08 / Ernst '08]
3 frames/second

CPU/SIMD [Hirschmüller '08]
0.25 frames/second



New features on current GPU architectures

- Rapid development of GPU architecture
- Fermi architecture has many new features
 - Dual warp scheduler
 - Branch prediction
 - Concurrent kernel execution
 - Improved context switching
 - Significantly more bandwidth and computational power
- Investigate SGM implementations for new GPUs

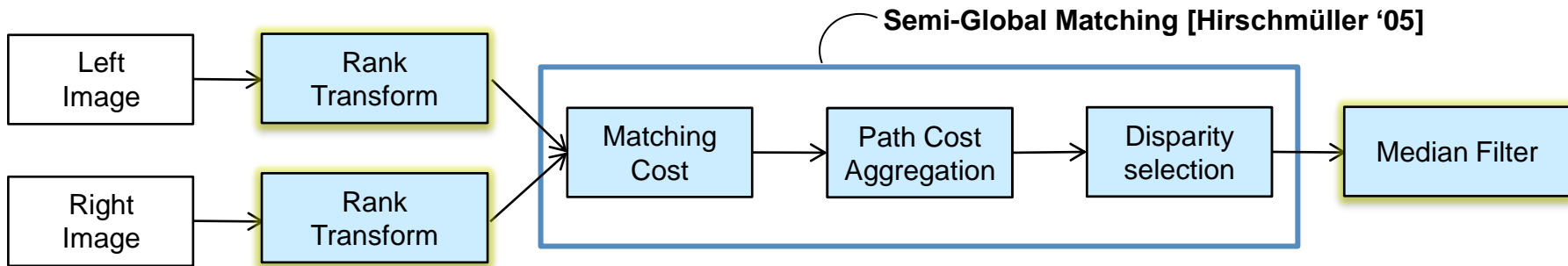
Performance limiting factors

- Software:
 - Effective memory bandwidth usage (i.e. aligned access)
 - Instruction throughput
- Hardware:
 - Latency of the memory interface
 - Latency of the arithmetic pipeline
 - issue rate: 1 instruction/cycle, but latency: several ten cycles
- *Both* has significant influence on performance
- Deep understanding of physical hardware necessary
 - Further reference: Slides by Volkov

Measures for high performance

- Ensure coalesced and aligned memory access
- Maximize data reuse (very little redundant memory access)
- High ratio of computational instructions to ancillary instructions
- Transfer coherent *chunks* of data to/from memory
- Keep the hardware pipeline filled
 - serial loop with independent arithmetic on local data
- Occupancy is not a good metric
 - Indicates the amount of resources occupied
 - *NOT* the effectiveness of usage

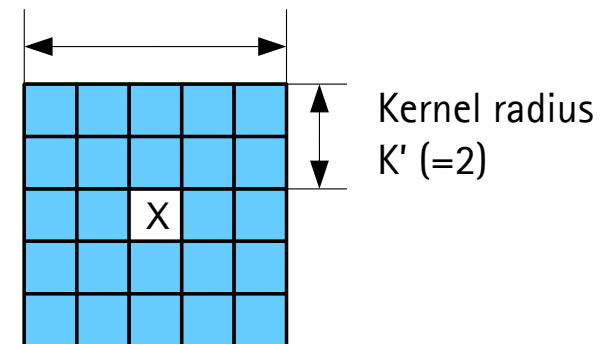
Semi-Global Matching



Rank transform und median filter

- 2D transformations
- non-separable
- requires access to local processing window

Kernel width: $K (=5)$



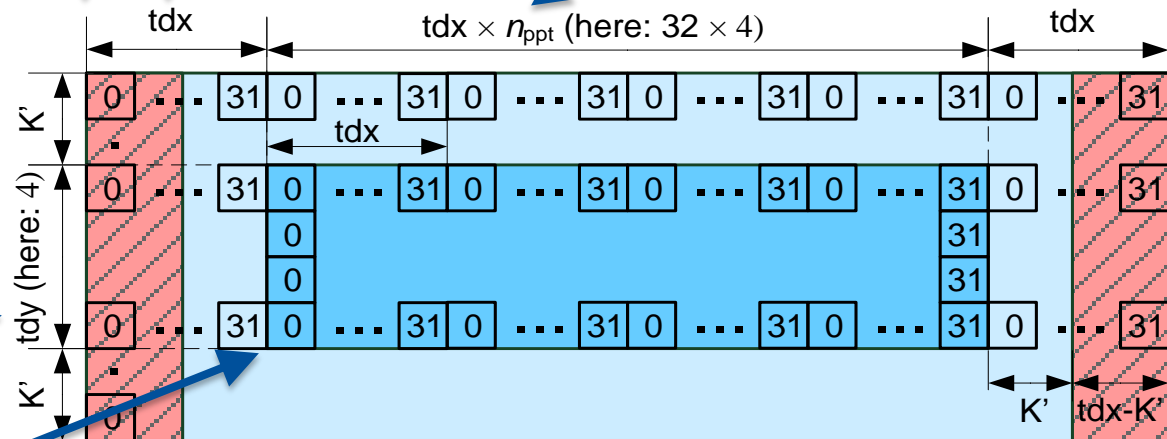
Non-separable 2D image transform Median Filter and Rank Transform

128 byte alignment
boundary
= no overhead

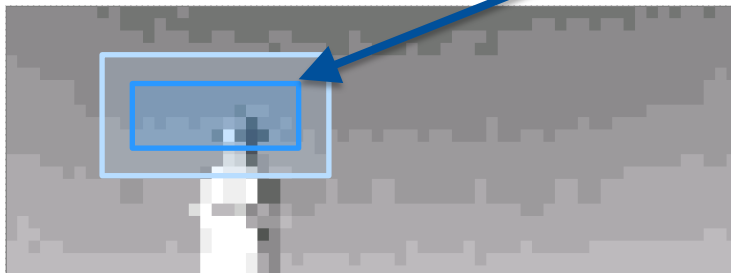
One warp = tdx in **parallel**
coalesced memory access

n_{ppt} pixel per thread **serially**
more computation per thread
= keep pipeline filled

tdy : increase
data reuse
more instructions
per ALU (cuda core)



local image window in shared memory



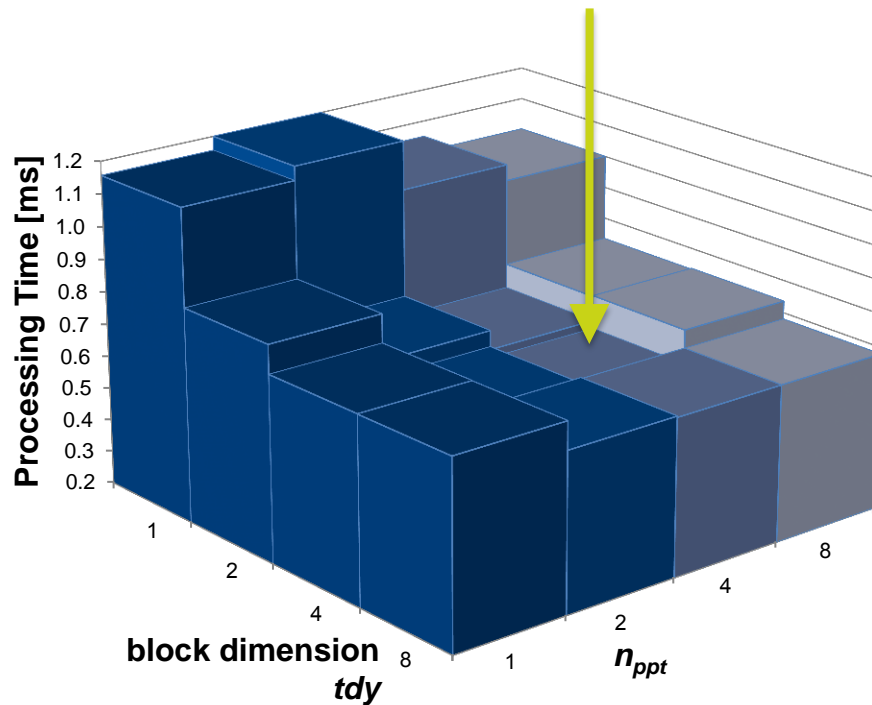
Extension of the separable convolution [Podlozhnyuk]

Parameter Study

Best configuration: $tdy = 4$ and $n_{ppt} = 4$

Performance: 0.64 ms

Speed-up > 2

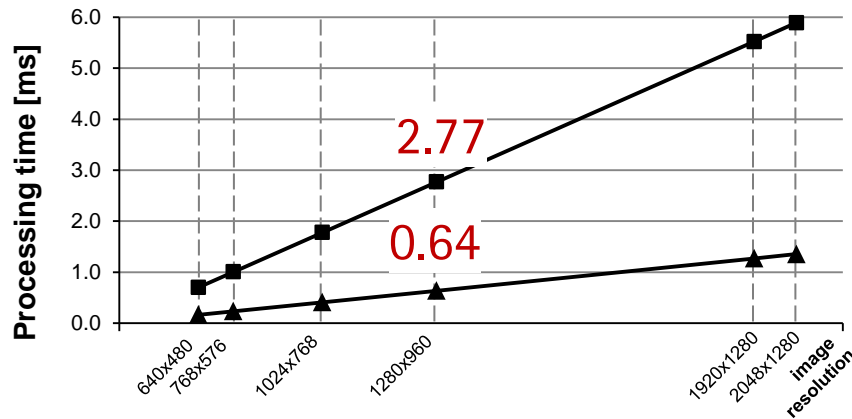


$tdx = 32$ (i.e. warp width)

1280 x 960 pixel image
3x3 median filter

Results (2D transform)

3x3 median filter (greyscale)

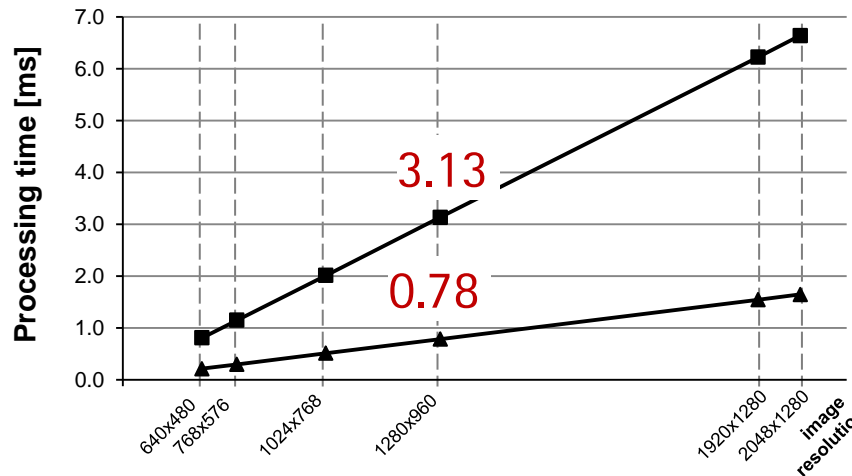


“Standard” implementation
using texture memory

proposed implementation
with optimal configuration set

Speed-Up: 4.3

9x9 rank transform (greyscale)

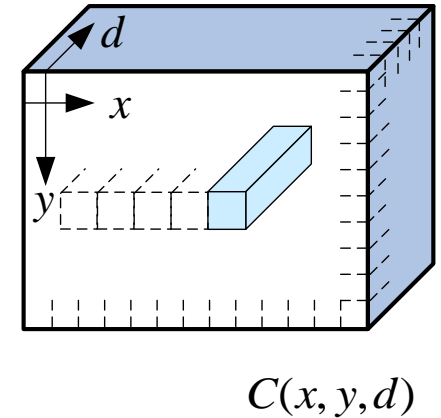
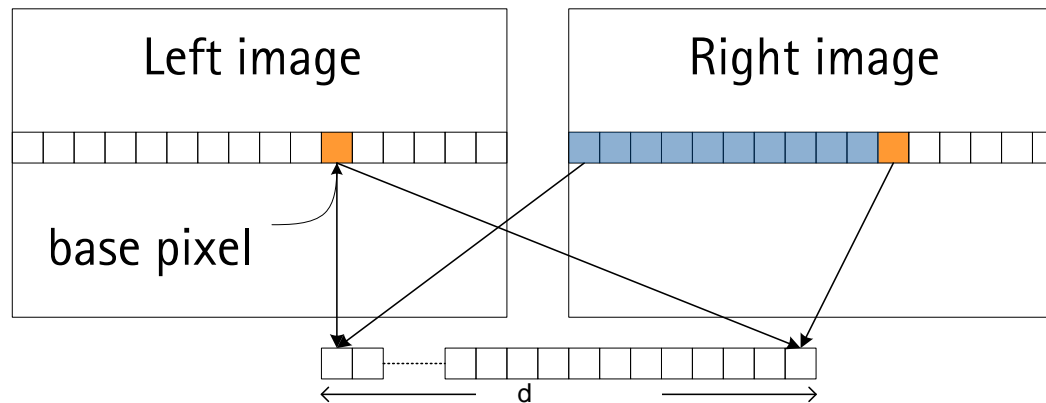
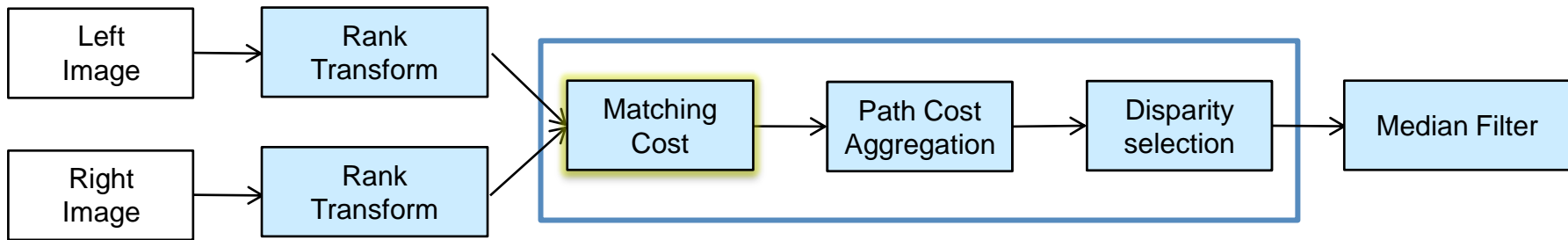


“Standard” implementation
using texture memory

proposed implementation
with optimal configuration set

Speed-Up: 4.0

Matching Cost Calculation



```

for (d=0;d<128;d++) {
    C[x,d] = |left[x] - right[x-d]|;
}
    
```

Matching Cost (MC) Implementation Options

Kernel	Time [ms]	Bandwidth / Max. Bandw.	Performance bound
(1) MC Unaligned	16.32	48.6 GB/s/ 144.0 GB/s	Memory Access Scheme

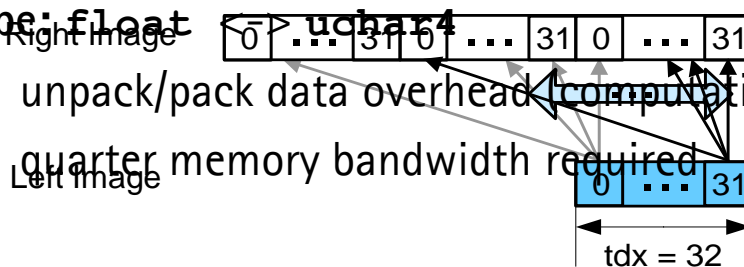
Unaligned: Each thread processes one point of $C(x,y,d)$

- Only $|\text{left}[x] - \text{right}[x-d]| \rightarrow$ not compute bound!

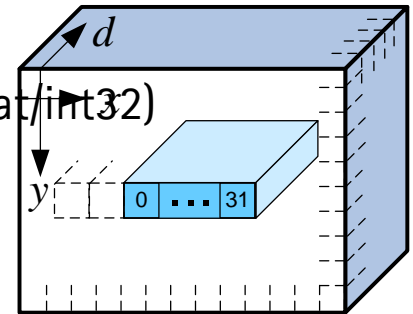
Proposed: Combination of parallel and serial with aligned memory access

Datatype: float

- unpack/pack data overhead (computation only efficient in float/int32)
- quarter memory bandwidth required

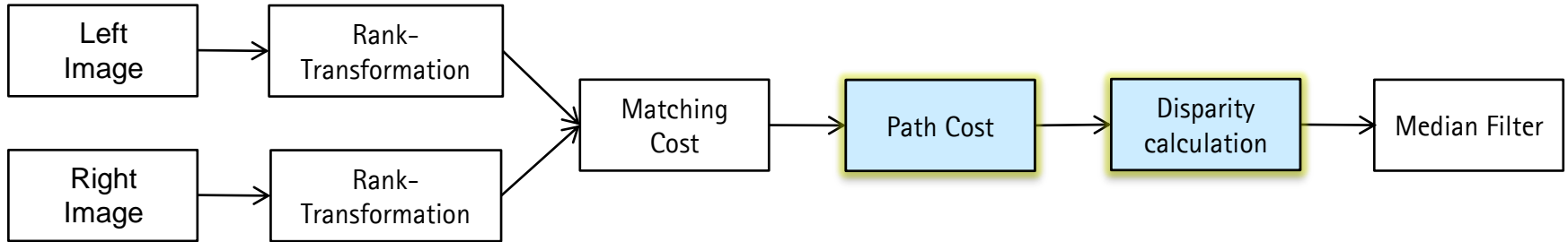


processed
in **tdy** and **serially**.
(pipeline full)



Threads process pixels in parallel
(aligned, coalesced memory access, parallelization)

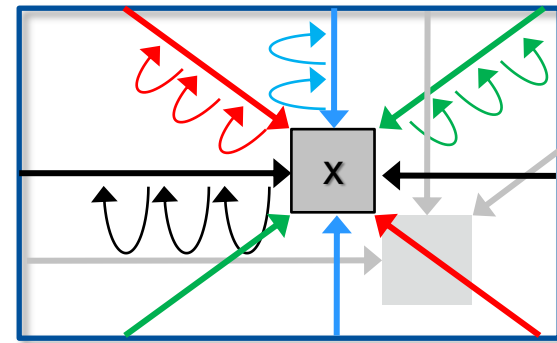
Path Cost Calculation



Main challenges imposed by Path Cost Calculation

- Main calculation is *recursive* and *not scan-aligned*
 - Values off all 8 paths must be kept
 - for the *next pixel along the path*
 - and until *all paths to a pixel are known*
- Parallelization concept which adheres to principles for fast implementation on the GPU

$$\begin{aligned}
 L_r(\mathbf{p}, d) = & C(\mathbf{p}, d) + \\
 & \min \{ L_r(\mathbf{p} - \mathbf{r}, d), \\
 & \quad L_r(\mathbf{p} - \mathbf{r}, d + 1) + P_1, \\
 & \quad L_r(\mathbf{p} - \mathbf{r}, d - 1) + P_1, \\
 & \quad \min_i \{ L_r(\mathbf{p} - \mathbf{r}, i) \} + P_2 \} - \\
 & \min_i L_r(\mathbf{p} - \mathbf{r}, i)
 \end{aligned}$$



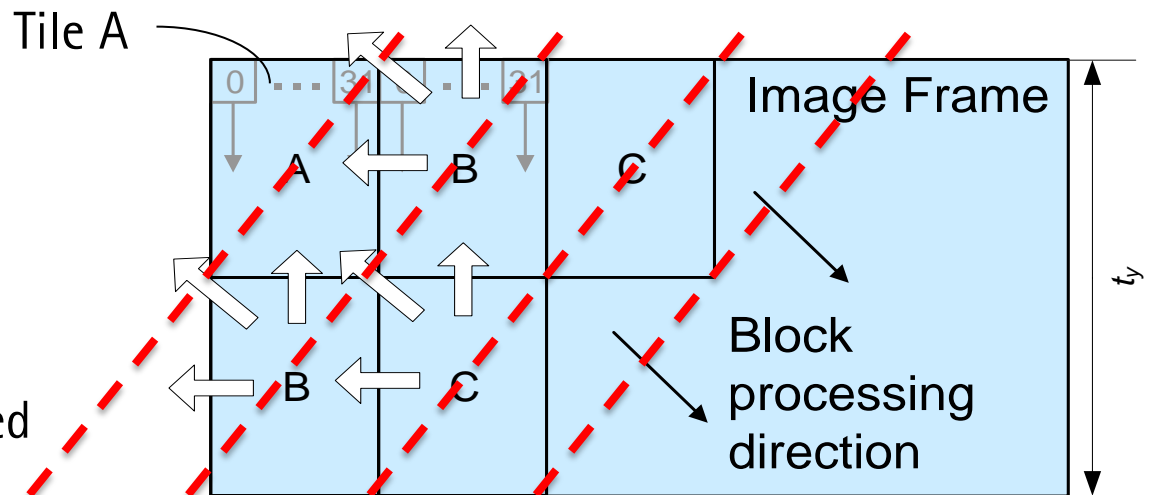
Path cost calculation

- Same parallelization scheme as for matching cost calculation
 - Major difference: Follow path direction serially

Example 

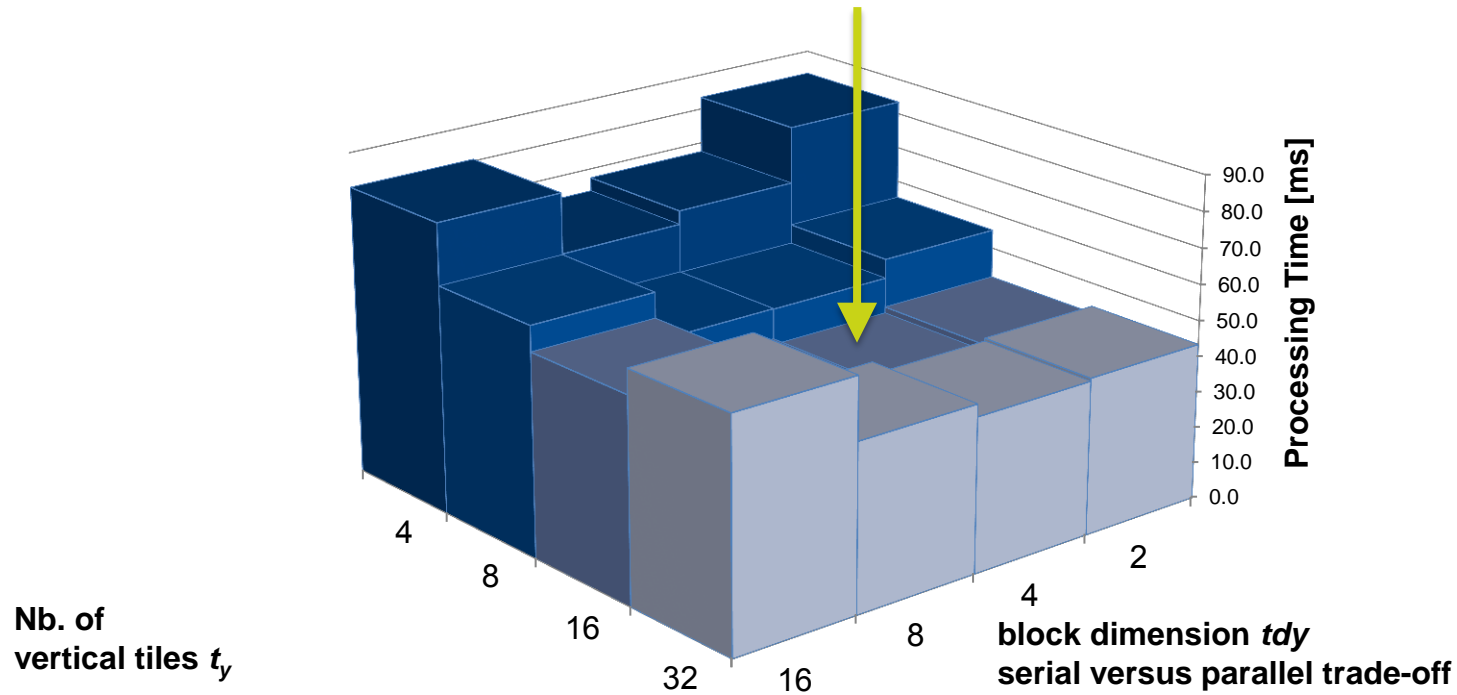
Both B s can be processed in parallel

Data dependencies:
 C can only be processed after A and both B s



Path Cost Calculation: Parameter Study

Best configuration: $t_y = 16$ and $tdy = 4$
 Performance: 39.81 ms
 Speed-Up: > 2



Path Cost Calculation: Results

- 1 path direction = 1 kernel
 - Not all streaming multiprocessors used
- Use concurrent kernel execution
 - Available with Fermi architectures
 - compensates inherently serial computation of the PC kernels

Kernel	Time [ms]	Bandwidth [GB/s]	Performance bound
Matching cost + Path cost all 8 path directions sequentially	75.68	20.9	Latency (pipeline is not always filled)

Summary of Results

Entire disparity estimation using semi-global matching

Implementation	Architecture	Com. Cap.	Image Size	Disparity depth	Processing time [ms]
Proposed here	Tesla C2050	2.0	640x480	128	16
Proposed here	Tesla C2050	2.0	1024x768	128	36

Observations

- Very fast implementation is sometimes a *black art*
 - A single code line can ruin performance
- Very deep knowledge of hardware behavior required
 - ALU and pipeline behavior (stalls, scheduler, etc.)
 - Physical memory properties and memory cache
- Hardware-oriented programming style necessary
- Nvidia should openly communicate this to programmers and provide relevant information

Conclusion

- Efficient parallelization schemes for SGM on the GPU
- Key enablers
 - Combination of parallel and serial implementation (parametrizable)
 - Serial implementation must be **local and independent**
 - Efficient, aligned, **block based** memory access
- Can serve as paradigm for programming styles (hardware oriented programming)