GPU - accelerated High Quality Semi-global Stereo Matching

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Introduction

Stereo matching is used to find corresponding pixels in a pair of images in order to calculate the depth of those pixels for 3D reconstruction.

Semi-global Stereo Matching [1]

- is a well-known approach in stereo vision
- runs quite fast with acceptable accuracy
- is widely-used in photogrammetry as well

Two steps

- Cost value creation
- Semi-global optimization

$$E(D) = \sum_{\mathrm{p}} \left(C(\mathrm{p}, D_{\mathrm{p}}) + \sum_{\mathrm{q} \in N_p} P_1 \mathrm{T}[|D_{\mathrm{p}} - D_{\mathrm{q}}| = 1] + \sum_{\mathrm{q} \in N_p} P_2 \mathrm{T}[|D_{\mathrm{p}} - D_{\mathrm{q}}| > 1] \right)$$

GPU Implementation

for our heavily templatized dense matcher with

- pixel types of 8, 16 bit (s/us), float
- handling of missing pixel
- census 9 cost function
- disparity predictor and shift predictor
- disparity range 15 (half warp optimized)
- cost values in float or half float
- cost aggregation along 8 paths
- matching direction forward / backward
- integration into a hierarchical workflow

based on the new Kepler (GK104+) features using

- CUB template library (http://github.com/NVlabs/cub/)

All kernels are fully templatized, intermediate results (census and prediction) reused.

Census Transform

Census 9 transform is done in shared memory [2], but with additional handling for missing pixel data.

$$R_T(P) = \bigotimes_{[i,j] \in D} \xi(P, P + [i,j])$$

along with a bit string of existing valid pixels

$$V(P) = \bigotimes_{[i,j] \in D} \nu(P, P + [i,j])$$

and $$\nu(P) = \begin{cases} 0, & I(P) \in \mathrm{I}_{invalid} \\ 1, & \text{else} \end{cases}$$

Census- and valid bitstrings are stored in three 32 bit chunks (96 bit) each, padded to four Uints (128 bit) each for performance reasons.

Usage of cub::SHL_ADD() for 32 bit segments further increases performance.

Normalized hamming distance in 32 bit chunks:

$$d = \frac{\_popc\big((refbits \& validbits)\,\hat{}\,(searchbits \& validbits)\big)}{\_popc(validbits)}$$

Cost Aggregation

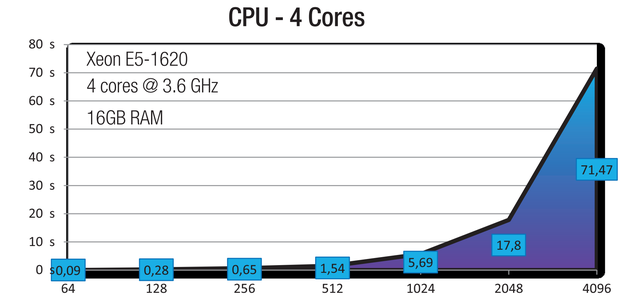
Disparity image aggregation is done in four kernels, each calculating two directions (e.g. North/South) with warp based functions like

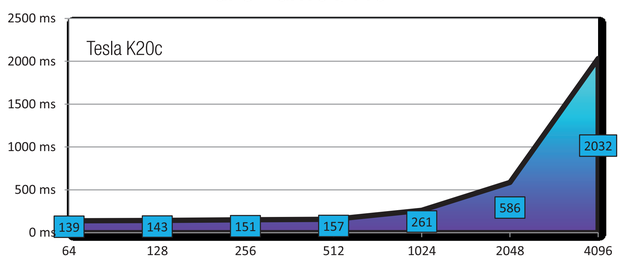
- __shfl()
- __ballot()
- __any() and
- cub::WarpReduce<datatype, 1, N>(Min())

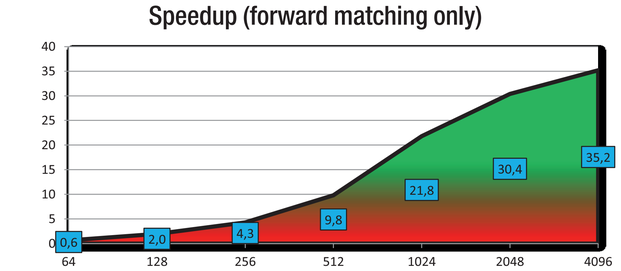
Disparities from cost selection uses subpixel accurate prediction (bilinear interpolation).

Calculation is done in float, storage is done in float or half float depending on template parameter.

Evaluation







Conclusion

- GPU implementation 20-39 times faster than CPU implementation (forward and backward matching, speedup higher for larger images)
- Kernel templates allow fine grained implementation (e.g. for more disparity ranges and matching functions) with minimal maintenance overhead
- Easily extensible to census 11 transform (120 bit) and disparity range 31
- CUB library is an excellent lightweight tool

[1] H. Hirschmüller: "Accurate and Efficient Stereo Processing by Semi-Global Matching and Mutual Information", CVPR, 2005

[2] C. D. Pantilie, S. Nedevschi: "Optimizing the Census Transform on CUDA enabled GPUs", ICCP, 2012

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