Bundled Depth-Map Merging for Multi-View Stereo

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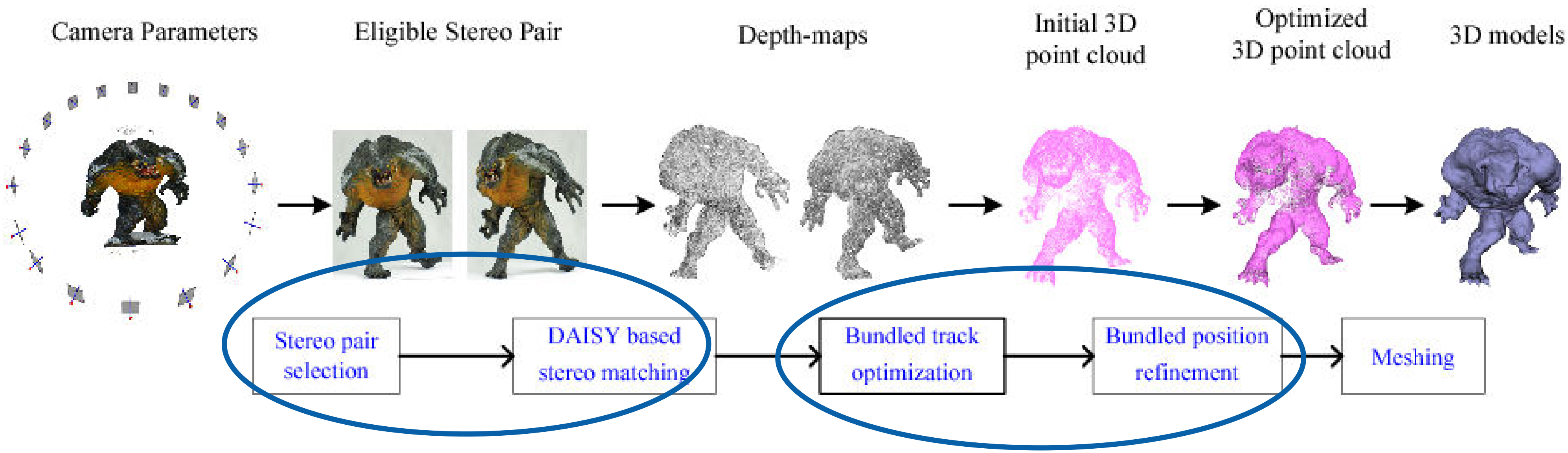
Outline

- Motivations
- Technique details
- Results
- Conclusions

Motivation

- MVS is crowded, but
  - Fast and accurate algorithm is still meaningful.
  - Application gamut not well studied
- Algorithms into several tech-categories
  - depth-map merging is typical and extensible; but
    - Requires sub-pixel stereo matching precision for accuracy
    - Challenges on merging inaccurate depth maps
- This paper proposes a bundle optimization based depth-map merging framework

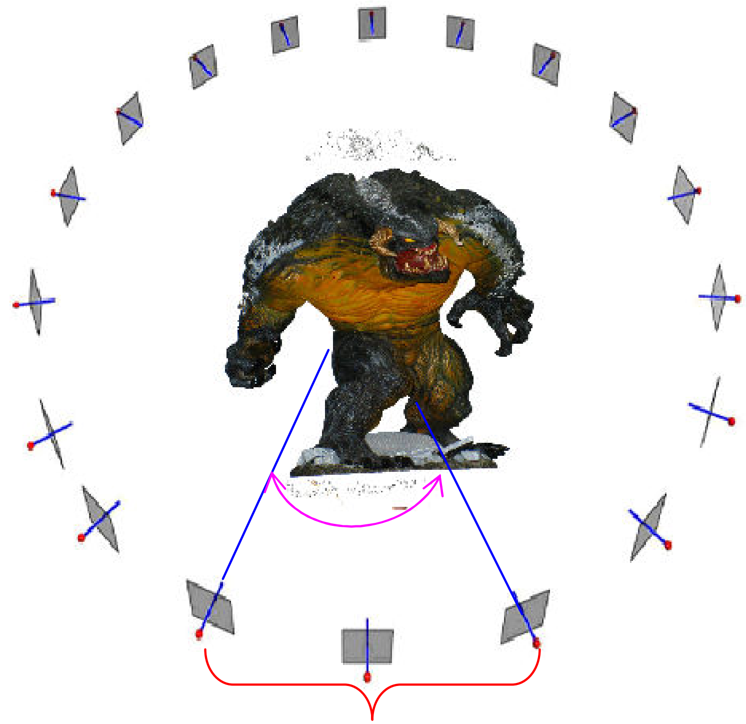
Framework



Stereo matching **Bundle optimization**

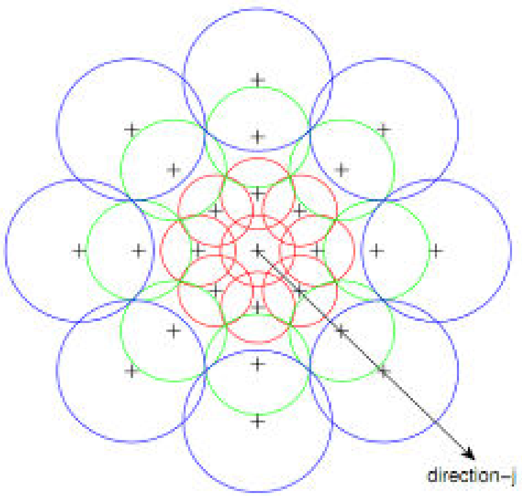
Stereo pair selection

- Not all image/stereo pairs are useful
  - Due to shear effect etc
- Based on three rules
  - Angle between view directions
    - In the range of 5~45
  - Distance between optical center
    - Remove too large or too small
  - Each view at most two pairs



Stereo matching

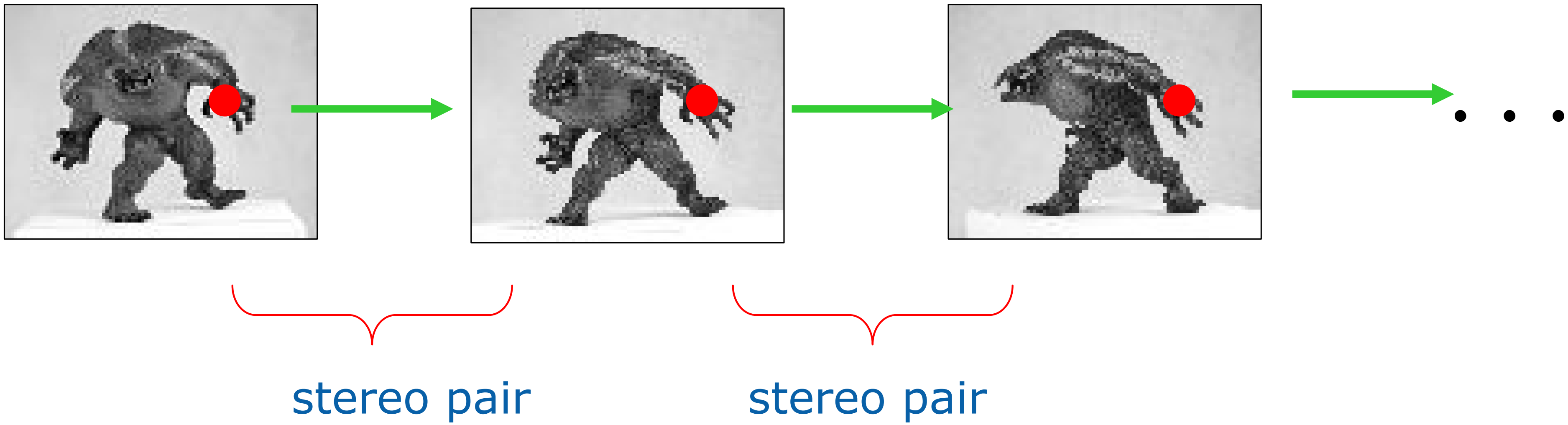
- Rectify stereo pairs
- For each pixel in a scan line of left image
  - Find correspondence in right image
  - Based on DAISY features
  - Using kd-tree to accelerate the search
  - Each pixel return top-K (=10) results
  - Scan-line optimization to keep intra-line order consistence
- Keep reliable matches



Track building and optimization

Track building

- Tracks: connected matching pixels from >= 3 views
- Depth-first search to find the tracks among stereo-pairs



Bundled track optimization (1)

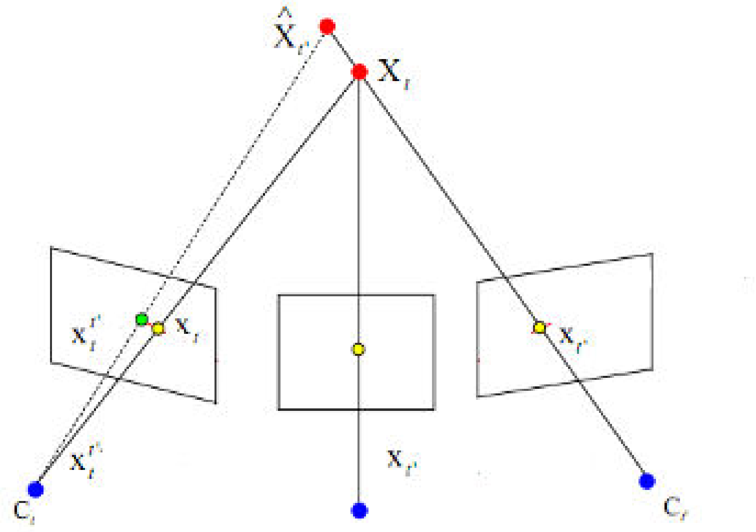
- Track optimization
  - A track => the same 3D point
  - Find: 3D points X such that

$$\min \sum_{x_i^k \in t_k} w(x_i^k) \| x_i^k - P_i^k \hat{X}^k \|,$$

  - $w(x)$ is weight function,

$$w(x_i^k) = \begin{cases} 1 & \text{if } \| x_i^k - P_i^k \hat{X}^k \| < \gamma, \\ 10 & \text{otherwise.} \end{cases}$$

  - Keep eligible tracks
    - reprojection error less than γ
    - β >= 3 views

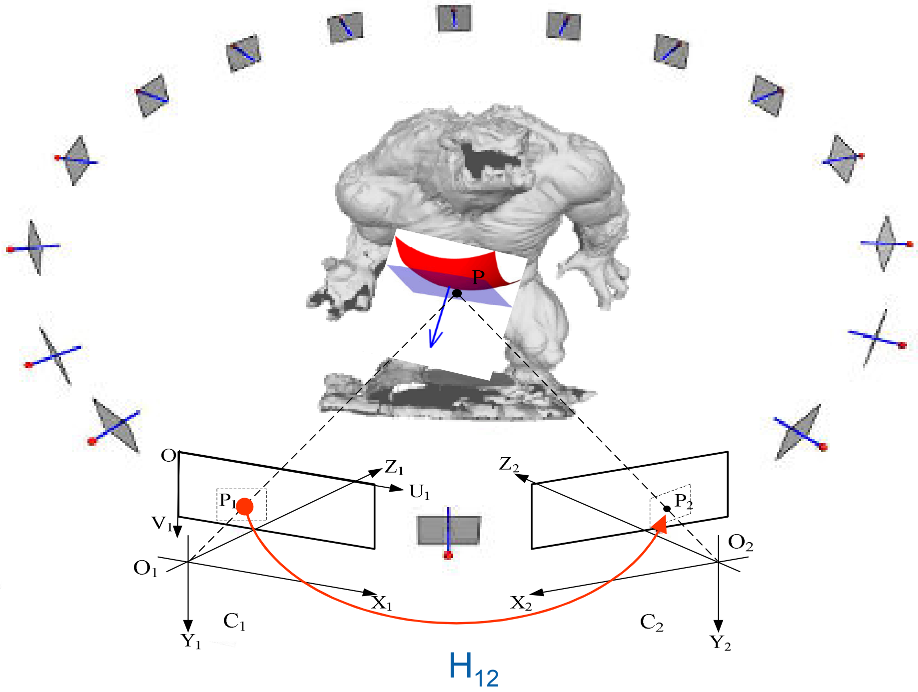


Bundled optimization (2)

- Refine the point position and estimate point normals with bounded optimization by photo-consistency (using L-BFGS-B)

$$E_k = \sum_{i,j \in t_k} \|DF_i(x) - DF_j(H_{ij}(x;\mathbf{n},d))\|,$$

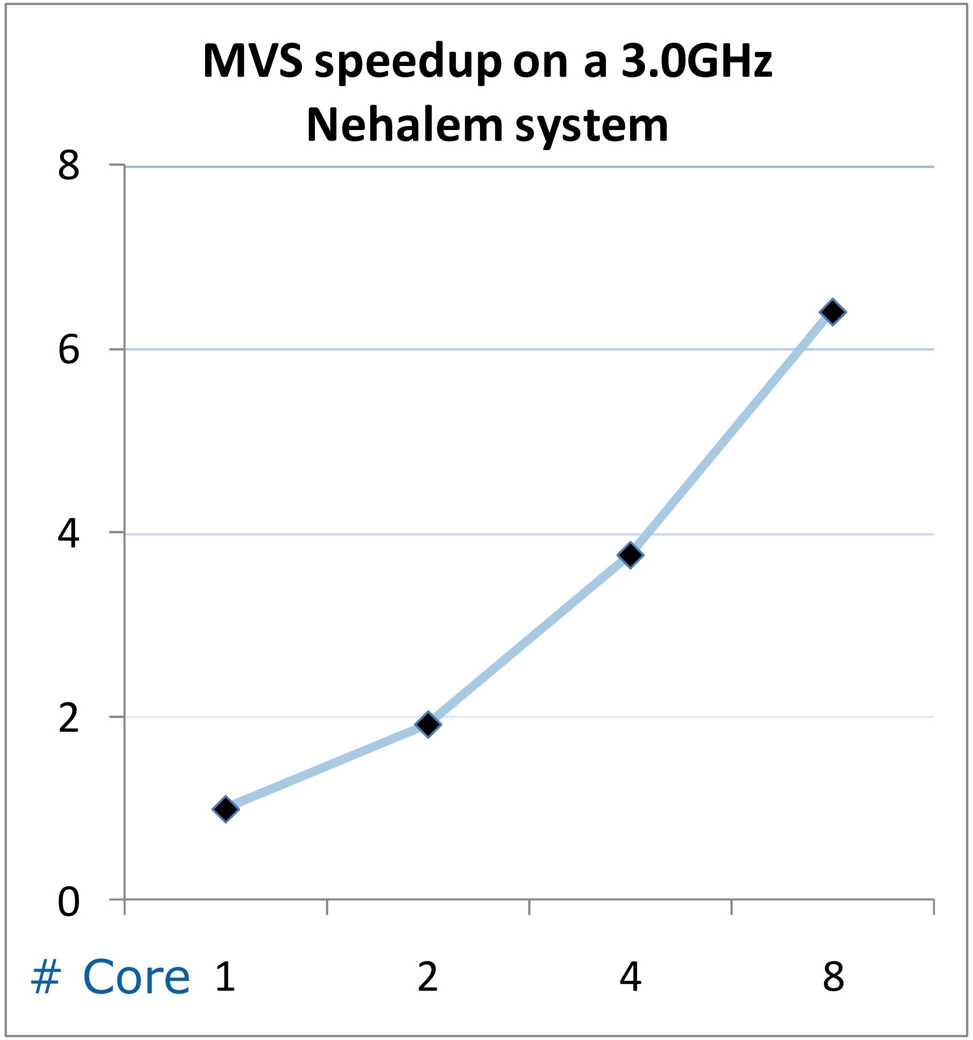
$$\begin{aligned} \min \quad & E_k, \\ s.t. \quad & (1)\ |\hat{x}_i - x_i| < \gamma, \\ & (2)\ \mathbf{n}_{ij} * \overrightarrow{X^i_{cam}O_i} / \|\overrightarrow{X^i_{cam}O_i}\| > 0.5, \end{aligned}$$



- Normal initialization
  - Initial normal with plane fitting or
  - Grid search from point view direction
- Benefits from bounded optimization
  - Less function evaluation
  - Fast convergence

Implementation

- CPU: multi-core, core i7
- Code: all in C/C++
- Fine-grained code optimization
  - SIMD for hotspots
    - Kdtree, DAISY, etc
  - Data-level parallelization
    - Scanline in stereo match
    - Tracks in track-opt
    - 3D Points in refinement
- A typical 32, 2Mpix dataset, took less than 3min



Results on Middlebury

- Performances:
  - Very high accuracy:
    - dinoRing result ranked within top 5
    - Comparable results on templeRing
  - One of the most efficient methods among non-GPU methods

Dataset	Accuracy	Completeness	Time (s)
dinoRing	0.43mm	99.7%	354
templeRing	0.64mm	98.2%	213

Note:
- During writing, use a 8-core core2duo.
- Better performance with Core i7.

Results on Real Datasets

Monster

34, 2Mpix

~25cm high

Complex surface

Example images and reconstruction results of the *Monster* dataset.

SculptFace

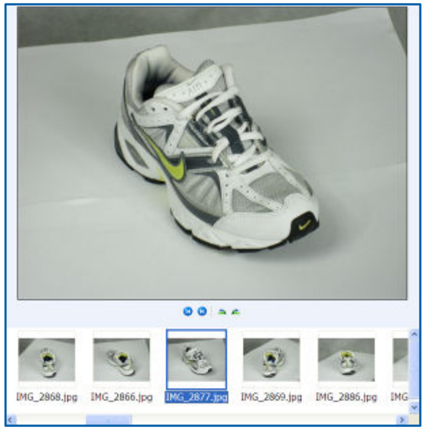
14, 6Mpix

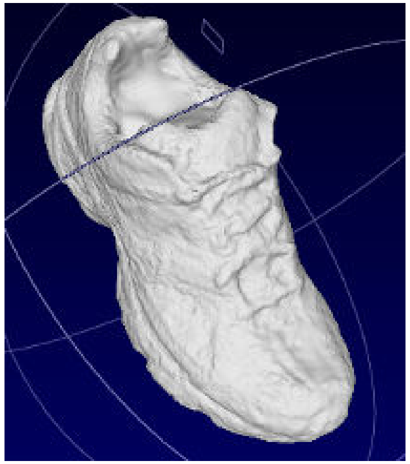
~1m high

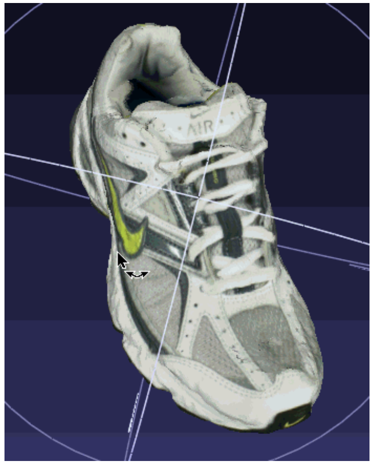
Highlight/metal surface

Example images and reconstruction results of the *SculptFace* dataset.

More Results





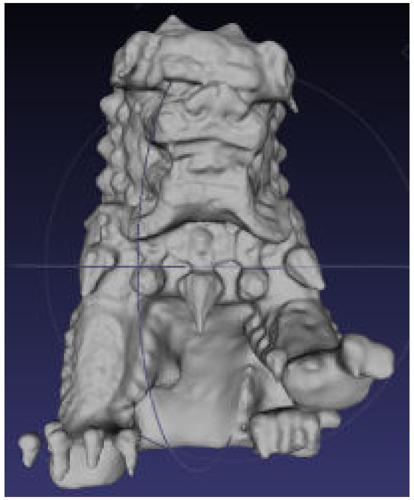


NikeShoe: 26, 4M pixel photos
Gum, Leather & Cloth, 23cm

Lion: 17, 6M pixel

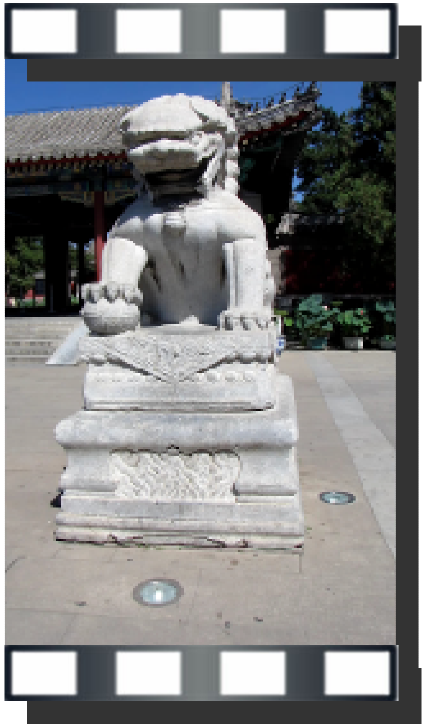
Iron, ~1.2m high

Large highlight area



Reconstructed surface **Textured model**

Results from video input



Input: ~1min HD video around a marble lion (Height/Width: ~2m/1m)

Reconstructed surface

Textured model

Conclusions

- Contributions
  - A bundle optimization framework for fast and accurate depth-map merging
  - Study MVS on complex/non-Lambertian/highlight surface
  - Introduce DAISY for MVS (both stereo matching and photo consistency optimization)
  - Parallel processing friendly and scalable well

Dataset available at http://sites.google.com/site/leeplus/bmvs/

Thank you!