Dense Methods 1: Stereo

CSE P576

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Dense Methods I: Stereo

- Stereo matching, local + global optimization
- Multi-view stereo, geometry representations
- Photometric Stereo
Application: Photo Collections → 3D

- Generate detailed 3D model (e.g., depth values at every pixel in input images)

[Y. Furukawa PMVS ]
Application: Remote Sensing

- Mars Reconnaissance Orbiter
- Launched 2005, ~13 orbits / earth day
- HIRISE camera pixels are $1 \mu$ radian (0.3m at 300km)
- MARCI camera has 5 visible + 2 UV bands, lower res

Image credit: NASA/JPL
Application: Remote Sensing

- Martian surface elevation map

Image credit: NASA/JPL/University of Arizona/USGS
Application: Remote Sensing

- Martian surface detail
Epipolar Geometry

- A point in one view may lie on a line in the 2nd

Position in image 2 depends on the **depth** of the 3D point
2-view Stereo

- Camera motion only, points constrained to epipolar lines

[Images of stereo view showing point correspondences and epipolar lines with ID Search labels]
Stereo Camera Configuration

- Humans and many stereo cameras have parallel optical axes
Axis Aligned Stereo

• A common stereo configuration has camera optical axes aligned, with cameras related by a translation in the $x$ direction

📝 5.1
Stereo Matching

• In a standard stereo setup, where cameras are related by translation in the x direction, epipolar lines are horizontal.

- Stereo algorithms search along scanlines for matches.
- Distance along the scanline (difference in x coordinate) for a corresponding feature is called \textit{disparity}.

\[ 5.2 \]
Disparity and Depth: R
Disparity and Depth: L
Figure 11.1
Stereo reconstruction techniques can convert (a–b) a pair of images into (c) a depth map (http://vision.middlebury.edu/stereo/data/scenes2003/) or (d–e) a sequence of images into (f) a 3D model (http://vision.middlebury.edu/mview/data/). (g) An analytical stereo plotter, courtesy of Kenney Aerial Mapping, Inc., can generate (h) contour plots.

Disparity and Depth: R+L

[ D. Scharstein ]
Effect of Window Size

- Larger windows $\rightarrow$ smoothed result
Anaglyph

- Stereo pair with images encoded in different color channels
Stereo Displays

- Field sequential (shutter) glasses transmit alternate left/right image at 120Hz

Lenticular lenses send different images directly to each eye, without the need for glasses
Stereo Displays

- VR headsets send L/R images directly to each eye
Stereo Rectification

- If the optical axes are not aligned, we can rotate the images (homography) until they are perpendicular to the baseline.
Stereo Rectification

- Transform (rotate) images so that epipolar lines are horizontal

[ Loop Zhang 1999 ]
Occlusions

• Sometimes a point in image 1 does not appear in image 2, or vice-versa (this is called an occlusion)

• Occlusions cause gaps in the stereo reconstruction

• Matching is difficult nearby as aggregation windows often overlap the occluded region
Edge Aware Stereo

- Occlusions and depth discontinuities cause problems for stereo matching, as aggregation windows overlap multiple depths.

- Segmentation-based stereo approaches aim to solve this by trying to guess the depth edges (e.g., joint segmentation and depth estimation [Taguchi et al 2008]).
Ordering Constraint

- If point B is to the right of point A in image 1, the same is usually true in image 2.

Not always, e.g., if an object is wholly within the ray triangle generated by A.
• Note that the ordering constraint is still maintained in the presence of occlusions
Optimal Scanline Mapping

• We can imagine a mapping between left and right scanlines
• If we assume the ordering constraint this must be monotonic, but there may be step changes (due to occlusions)
• How can we find the best monotonic sequence mapping left to right scanlines?

![Diagram of scanline mapping]

Left scanline

Right scanline
Dynamic Programming

- At each point, we may make one of 3 moves: left/right occlusion (higher cost), or sequential correspondence (lower cost based on patch SSD)

Look for a path from top left to bottom right with the lowest cost

[ Cox et al 1996 ]
Dynamic Programming

- We need not consider all possible paths, as we only need to know the lowest cost path for reaching each state

[ Cox et al 1996 ]
Stereo Cost Functions

- Energy function for stereo matching based on disparity $d(x,y)$
- Sum of data and smoothness terms
  \[ E(d) = E_d(d) + \lambda E_s(d) \]
- Data term is cost of pixel $x,y$ allocated disparity $d$ (e.g., SSD)
  \[ E_d(d) = \sum_{(x,y)} C(x, y, d(x, y)) \]
- Smoothness cost penalises disparity changes with robust $\rho(.)$
  \[ E_s(d) = \sum_{(x,y)} \rho(d(x, y) - d(x + 1, y)) + \rho(d(x, y) - d(x, y + 1)) \]
- This is a Markov Random Field (MRF), which can be solved using techniques such as Graph Cuts

[Szeliski B5]
Stereo Comparison

- Global vs Scanline vs Local optimization

Ground truth

Graph Cuts
[ Kolmogorov Zabih 2001]

Dynamic Programming

SSD 21px aggregation

[Scharstein Szeliski 2002]
Multiview Stereo

- Plane sweep, volumetric, depth map merging

[Szeliski 11.6]
Multiview Stereo

- Use information from N>2 views to form a dense 3D reconstruction

[ Y. Furukawa PMVS ]
Multiview Stereo

- Search along epipolar lines to find good matches in N views
Plane Sweep Stereo

$H_{12}(d)$

$d=N$

$d=2$

$d=1$
Plane Sweep Stereo

• Warp images using a set of planes in front of the camera

5.4

Virtual camera

Homography:

\[ u = H x \]

Input image \( k \)

Collins and Anandan (1994) and Szeliski (1996) propose methods to do this. The plane sweep algorithm is presented in Szeliski et al. (1999) and Hanna (1997). This method can be used to compute the homographies of the sweep planes (Fig. 2.68) and the warps the scene through the sweep (Fig. 2.69). The depth information is used to zip up the virtual camera (Fig. 2.70). The disparity space image is used to recover the 3D points of interest (Fig. 2.71).

Anandan and Coughlan (1999) and Coughlan and Golland (1999) present a method to compute the disparity map of the scene. The disparity map is used to compute the homographies of the sweep planes (Fig. 2.68) and the warps the scene through the sweep (Fig. 2.69). The depth information is used to zip up the virtual camera (Fig. 2.70). The disparity space image is used to recover the 3D points of interest (Fig. 2.71).
Plane Sweep Stereo

• Warp images using a set of planes in front of the camera

Try out PlaneSweep.ipynb from the course webpage
Volumetric Stereo

- Discretise the scene using a grid of voxels
- Infer occupancy and colour of voxels by projecting to images
• Idea: visit all voxels in order, keep only photo-consistent voxels

What is wrong with this idea?
Space Carving

- Space carving finds a voxel reconstruction that is consistent with the input images, taking into account visibility.

  - Initialise a volume containing the true scene.
  - Choose a voxel $v$ on the surface.
  - Project $v$ to all views where visible.
  - If $v$ is not photo-consistent, remove it from the volume.
  - Repeat until all voxels are photo-consistent.

Figure 11: Shaded (top) and colored (bottom) voxel models of a dinosaur toy at different resolutions.

Figure 12: Comparison of voxel coloring and silhouette-based reconstruction. Input image (a) is shown next to reconstructions rendered at the same viewpoint. (b): voxel coloring reconstruction. (c): silhouette-based reconstruction.

~1k voxels

~70k voxels
Silhouette Intersection

- Consider the case of binary images (silhouettes)
- Voxel is part of the object if it lies in the silhouette in all views

Project volumes from each silhouette back into scene and intersect

Voxel reconstruction is larger than object

[Seitz / Lazebnik]
Silhouette Intersection

- The intersection of back-projected silhouettes is called the **visual hull**, it is more accurate with increasing # views

[Ben Tordoff / Mathworks]
Depth Map Merging

- Idea: Nearby images have the most reliable stereo matches
- If we have a lot of images/pixels, we may not need to perform wide baseline matching

[ http://vision.middlebury.edu/mview ]
Depth Map Merging

- Select subsets of images and compute high confidence depth maps (e.g., keep only low SSD matches)
- Merge depth maps using robust fusion, e.g., using signed distance functions [Curless Levoy 1996]

*Figure 3.7: The effects of the number of input images after depthmap merging for the two datasets. The algorithm by Goesele, Curless, and Seitz is used [80]. (Figure courtesy of Goesele et al.)

3.1.3 MRF Depthmaps

Despite the use of the robust photo-consistency function in the previous section, the peak of a photo-consistency curve may not correspond to the true depth in challenging cases. In the presence of severe occlusions, there may not exist a corresponding match in most other images. A standard solution for these problems is to enforce spatial consistency, under the assumption that neighboring pixels have similar depth values, where Markov Random Field (MRF) is a very popular and successful formulation for the task. The MRF depthmap formulation [120] can be seen as a combinatorial optimization problem, where an input depth range is discretized into a finite set of depth values. The problem is then to assign a depth label $k_p$ from the label set to each pixel $p$, while minimizing the following cost function:

$$E(\{k_p\}) = \sum_p \Phi(k_p) + \sum_{(p,q) \in N} \Psi(k_p, k_q).$$

(3.2)

The first summation is over all the pixels in the image, while the second summation is over all the pairs of neighboring pixels denoted
• Depth map merging is practical for photo collections:
• Adaptable to complex geometry and large-scale scenes
• Robust to varied imagery and noise — select only subsets with good matches (don’t try to match everything)
Neural Scene Representation

- Neural Radiance Fields, ~10s of input views

matthewtancik.com/nerf
Photometric Stereo

- We can also get 3D information about the scene using one camera and multiple lights

- The most straightforward case of photometric stereo is to assume Lambertian reflectance

\[ 5.5 \]
Photometric Stereo by Example

- Use object of known geometry, match colour patterns
Non-rigid Photometric Stereo with Colored Lights

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Next Lecture

• Depth, Flow