Multi-View Geometry: Find Corresponding Points
(New book: Ch7.4, 7.5, 7.6
Old book: 11.3-11.5)

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CS 6320 Spring 2013

Credit for materials: Trevor Darrell, Berkeley, C280, Marc Pollefeys, UNC/ETH-Z, CS6320 S012, Andrew Zisserman, MVG Book
Excellent Website:
http://vision.middlebury.edu/stereo/

Welcome to the Middlebury Stereo Vision Page, formerly located at www.middlebury.edu/stereo. This website accompanies our
taxonomy and comparison of two-frame stereo correspondence algorithms [1]. It contains:

- An on-line evaluation of current algorithms
- Many stereo datasets with ground-truth disparities
- Our stereo correspondence software
- An on-line submission script that allows you to evaluate your stereo algorithm in our framework

How to cite the materials on this website:
We grant permission to use and publish all images and numerical results on this website. If you report performance results, we request
that you cite our paper [1]. Instructions on how to cite our datasets are listed on the datasets page. If you want to cite this website,
please use the URL 'vision.middlebury.edu/stereo'.

References:

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not necessarily reflect the views of the National Science Foundation.
Stereo reconstruction: main steps

– Calibrate cameras
– Rectify images
– Compute disparity
– Estimate depth
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- Calibrate cameras
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Correspondence problem

Multiple match hypotheses satisfy epipolar constraint, but which is correct?

Figure from Gee & Cipolla 1999
Correspondence problem

• Beyond the hard constraint of epipolar geometry, there are “soft” constraints to help identify corresponding points
  – Similarity
  – Uniqueness
  – Ordering
  – Disparity gradient
Correspondence problem

• Beyond the hard constraint of epipolar geometry, there are “soft” constraints to help identify corresponding points
  – Similarity
  – Uniqueness
  – Ordering
  – Disparity gradient

• To find matches in the image pair, we will assume
  – Most scene points visible from both views
  – Image regions for the matches are similar in appearance
Your basic stereo algorithm

Adapted from Li Zhang
Your basic stereo algorithm

For each epipolar line:
Your basic stereo algorithm

For each epipolar line:
   For each pixel in the left image

Adapted from Li Zhang
Your basic stereo algorithm

For each epipolar line:
   For each pixel in the left image
      • compare with every pixel on same epipolar line in right image

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For each epipolar line:

For each pixel in the left image

- compare with every pixel on same epipolar line in right image
- pick pixel with minimum match cost

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Improvement: match windows
  • This should look familiar...
  • E.g. SSD, correlation etc.

Adapted from Li Zhang
Stereo matching

- Search is limited to epipolar line (1D)
- Look for “most similar pixel”

```matlab
for x=1:w,
    for y=1:h,
        bestdist=inf;
        for i=-dr:0,
            if (dist(pix(x,y),pix(x+i,y))<bestdist)
                d(x,y)=i; best=sim(pix(x,y),pix(x+i,y)); end
            end
        end
    end
end
```
Stereo matching algorithms

• Match Pixels in Conjugate Epipolar Lines
  – Assume brightness constancy
  – This is a tough problem
  – Numerous approaches
    • dynamic programming [Baker 81,Ohta 85]
    • smoothness functionals
    • more images (trinocular, N-ocular) [Okutomi 93]
    • graph cuts [Boykov 00]
  – A good survey and evaluation:
    – http://vision.middlebury.edu/stereo/
Correspondence using Discrete Search

 Criterion function:

Left

Right

scanline

error

disparity
Comparing image regions

Compare intensities pixel-by-pixel

Similarity measures

Census

\[ C_I(i, j) = (I(x + i, y + j) > I(x, y)) \]

<table>
<thead>
<tr>
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\[ \begin{array}{ccc}
0 & 0 & 0 \\
0 & 1 & 1 \\
1 & 1 & 1 \\
\end{array} \]

\[ \text{[00001111]} \]
only compare bit signature

(Real-time chip from TYZX based on Census)
Sum of Squared Differences (SSD)

$w_L$ and $w_R$ are corresponding $m$ by $m$ windows of pixels.

We define the window function:

$$W_m(x, y) = \{u, v \mid x - \frac{m}{2} \leq u \leq x + \frac{m}{2}, y - \frac{m}{2} \leq v \leq y + \frac{m}{2}\}$$

The SSD cost measures the intensity difference as a function of disparity:

$$C_r(x, y, d) = \sum_{(u, v) \in W_m(x, y)} [I_L(u, v) - I_R(u - d, v)]^2$$
Example

Feature Matching

Evaluate NCC for all features with similar coordinates

e.g. \((x', y') \in \left[ x - \frac{w}{10}, x + \frac{w}{10} \right] \times \left[ y - \frac{h}{10}, y + \frac{h}{10} \right]$

Keep mutual best matches
Still many wrong matches!
Example ctd

Feature Example

Gives satisfying results for small image motions
Example image pair – parallel cameras
Intensity profiles

- Clear correspondence between intensities, but also noise and ambiguity
Dense correspondence algorithm

Parallel camera example – epipolar lines are corresponding rasters
Dense correspondence algorithm

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Parallel camera example – epipolar lines are corresponding rasters

Search problem (geometric constraint): for each point in the left image, the corresponding point in the right image lies on the epipolar line (1D ambiguity)

Disambiguating assumption (photometric constraint): the intensity neighbourhood of corresponding points are similar across images

Measure similarity of neighbourhood intensity by cross-correlation
Correspondence problem

Neighborhood of corresponding points are similar in intensity patterns.

Source: Andrew Zisserman
Slide the window along the epipolar line until $w \cdot w'$ is maximized.
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Slide the window along the epipolar line until \( w \cdot w' \) is maximized.

Normalized Correlation: minimize \( \theta \) instead.

Slide the window along the epipolar line until $w \cdot w'$ is maximized.

Normalized Correlation: minimize $\theta$ instead. $\Leftarrow$ Minimize $|w-w'|^2$. 
Cross-correlation of neighbourhood regions

- Left and right windows encoded as vectors $w$ and $w'$
- Zero-mean vectors $(w - \bar{w})$ and $(w' - \bar{w}')$
- Normalized cross-correlation:
  \[
  C(d) = \frac{1}{||w - \bar{w}||} \frac{1}{||w' - \bar{w}'||} [(w - \bar{w}) \cdot (w' - \bar{w}')].
  \]
- Advantage: Invariant to intensity differences: Invariant to affine intensity transformation $I' = \alpha I + \mu$
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Correlation-based window matching
Correlation-based window matching

left image band \((x)\)

right image band \((x')\)

Source: \(\)
Correlation-based window matching

Source: Andrew Zisserman
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Correlation-based window matching

Source: Andrew Zisserman
Textureless regions

Source: Andrew Zisserman

Grauman
Textureless regions

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Textureless regions are non-distinct; high ambiguity for matches.

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Textureless regions

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Textureless regions are non-distinct; high ambiguity for matches, → wrong matches.
Effect of window size

Source: Andrew Zisserman
Effect of window size

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Effect of window size

Source: Andrew Zisserman
Problems with window matching

Patch too small?
Patch too large?

Can try variable patch size [Okutomi and Kanade],
or arbitrary window shapes [Veksler and Zabih]
Effect of window size

Want window large enough to have sufficient intensity variation, yet small enough to contain only pixels with about the same disparity.
Effect of window size

Want window large enough to have sufficient intensity variation, yet small enough to contain only pixels with about the same disparity.

Figures from Li Zhang
Problems?

• Ordering
• Occlusion
• Foreshortening

Solutions:
• Formulate Constraints
• Use more than two views
• Smart solutions vs. “brute force” searches with statistics
Exploiting scene constraints
Additional geometric constraints for correspondence

[Faugeras, pp. 321]

• **Ordering of points:**
  Continuous surface: same order in both images.

• Is that always true?
The Ordering Constraint

In general the points are in the same order on both epipolar lines.
The Ordering Constraint

But it is not always the case..
Ordering constraint

surface slice

surface as a path

occlusion left

occlusion right
Stereo matching

Similarity measure (SSD or NCC)

Constraints
- epipolar
- ordering
- uniqueness
- disparity limit

Trade-off
- Matching cost (data)
- Discontinuities (prior)

Consider all paths that satisfy the constraints
pick best using dynamic programming
Stereo matching

Consider all paths that satisfy the constraints
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Constraints
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Similarity measure
(SSD or NCC)

Optimal path
(dynamic programming)
Dynamic Programming (Baker and Binford, 1981)

Find the minimum-cost path going monotonically down and right from the top-left corner of the graph to its bottom-right corner.

- Nodes = matched feature points (e.g., edge points).
- Arcs = matched intervals along the epipolar lines.
- Arc cost = discrepancy between intervals.
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% Loop over all nodes \((k, l)\) in ascending order.
for \(k = 1\) to \(m\) do
  for \(l = 1\) to \(n\) do
    % Initialize optimal cost \(C(k, l)\) and backward pointer \(B(k, l)\).
    \(C(k, l) \leftarrow +\infty; B(k, l) \leftarrow \text{nil};\)
    % Loop over all inferior neighbors \((i, j)\) of \((k, l)\).
    for \((i, j)\) \in \text{Inferior} – \text{Neighbors}(k, l) do
      % Compute new path cost and update backward pointer if necessary.
      \(d \leftarrow C(i, j) + \text{Arc} – \text{Cost}(i, j, k, l);\)
      if \(d < C(k, l)\) then \(C(k, l) \leftarrow d; B(k, l) \leftarrow (i, j)\) endif;
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The Ordering Constraint

In general the points are in the same order on both epipolar lines.
The Ordering Constraint

But it is not always the case..
Forbidden Zone

\[ m_1 \quad m_2 \]

\[ M \]
Forbidden Zone

\[ \text{Diagram showing: } m_1 n_1 \quad \text{and} \quad n_2 m_2 \]
Forbidden Zone

Forbidden Zone of M:
Violation of ordering constraints

m₁ n₁  n₂ m₂
Forbidden Zone

Forbidden Zone of M:
Violation of ordering constraints

Practical applications:
- Object bulges out: ok
- In general: ordering across whole image is not reliable feature
- Use ordering constraints for neighbors of M within small neighborhood only
Disparity map

\[ (x', y') = (x + D(x, y), y) \]
Hierarchical stereo matching

- Allows faster computation
- Deals with large disparity ranges

Downsampling (Gaussian pyramid)
Dynamic Programming (Ohta and Kanade, 1985)
Real-time stereo on graphics hardware

Ruigang Yang and Marc Pollefeys, UNC

- Computes Sum-of-Square-Differences
- Hardware mip-map generation used to aggregate results over support region
- Trade-off between small and large support window

140M disparity hypothesis/sec on Radeon 9700pro
e.g. 512x512x20 disparities at 30Hz

Shape of a kernel for summing up 6 levels
Stereo results

- Data from University of Tsukuba
- Similar results on other images without ground truth
Results with window correlation

Window-based matching (best window size)  Ground truth
Results with better method

State of the art method

Ground truth
Material I

• [http://vision.middlebury.edu/stereo/](http://vision.middlebury.edu/stereo/)

• (online stereo pairs and truth (depth maps))
• Stereo correspondence software: e.g. [http://vision.middlebury.edu/stereo/data/scenes2001/data/imagehtml/tsukuba.html](http://vision.middlebury.edu/stereo/data/scenes2001/data/imagehtml/tsukuba.html)
Material II

- Epipolar Geometry, Rectification:

- Stereo:

- 3D Reconstruction:
Additional Materials
Problem: Foreshortening

Window methods assume fronto-parallel surface at 3-D point.

Initial estimates of the disparity can be used to warp the correlation windows to compensate for unequal amounts of foreshortening in the two pictures [Kass, 1987; Devernay and Faugeras, 1994].
Why is cross-correlation such a poor measure in the second case?

1. The neighbourhood region does not have a “distinctive” spatial intensity distribution
2. Foreshortening effects
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imaged length the same
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2. Foreshortening effects

fronto-parallel surface
imaged length the same

slanting surface
imaged lengths differ
Three Views

The third eye can be used for verification..

Demo epipolar geometry
Three Views

The third eye can be used for verification..

Demo epipolar geometry
Three Views

The third eye can be used for verification.

Demo epipolar geometry
More Views (Okutami and Kanade, 1993)

New book: Ch7.6 p. 215: Pick a reference image, and slide the corresponding window along the corresponding epipolar lines of all other images, using inverse depth ($Z^{-1}$) relative to the first image as the search parameter.

Use the sum of correlation scores to rank matches: SSD used as global evaluation function: Find $Z^{-1}$ that minimizes SSD.
Multi-camera configurations

3 cameras give both robustness and precision

4 cameras give additional redundancy

3 cameras in a T arrangement allow the system to see vertical lines.

(illustration from Pascal Fua)
Normalized cross correlation

subtract mean: \( A \leftarrow A - \langle A \rangle, B \leftarrow B - \langle B \rangle \)

\[
NCC = \frac{\sum_i \sum_j A(i, j)B(i, j)}{\sqrt{\sum_i \sum_j A(i, j)^2} \sqrt{\sum_i \sum_j B(i, j)^2}}
\]

Write regions as vectors

\( A \rightarrow a, \quad B \rightarrow b \)

\[
NCC = \frac{a \cdot b}{|a||b|}
\]

\(-1 \leq NCC \leq 1\)

Source: Andrew Zisserman
Aggregation window sizes

Small windows
- disparities similar
- more ambiguities
- accurate when correct

Large windows
- larger disp. variation
- more discriminant
- often more robust
- use shiftable windows to deal with discontinuities

(Illustration from Pascal Fua)