Computer Vision II

Introduction - 16.04.2014

TECHNISCHE UNIVERSITÄT DARMSTADT

visual inference

Stefan Roth, 16.04.2014

Computer Vision II

TECHNISCHE UNIVERSITÄT DARMSTADT

- Lecturer:
  - Stefan Roth <sroth AT cs.tu-darmstadt...>
  - Office hours: Wednesdays, 13:45 - 14:45, S3|05, room 317
- Teaching Assistants:
  - Uwe Schmidt <uwe.schmidt AT gris.tu-...>
  - Tobias Plötz <tobias.ploetz AT gris.tu-...>
  - Office hours: TBA
- Course staff email: <cv2staff AT gris.tu-...>
  - Please use it for any questions, concerns etc.

Course Material

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- Course web page: goo.gl/glQ8Kh
  - Contains pointers to readings
- Moodle ("HRZ Moodle"): goo.gl/l028kx
  - Please make sure you are signed up!
  - Contains slides and homework assignments
- Mailing list (see webpage):
  - We will sign you up, if you leave/left us your email during the first class.
  - Otherwise, please sign up yourself!

Forum

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- There is a forum set up at the Fachschaft's website:
  http://www.fachschaft.informatik.tu-darmstadt.de/forum/viewforum.php?f=311
  - Please use it to ask questions of public interest.
  - You are encouraged to discuss with each other.
  - However: Please do not share solutions or give strong hints about the solutions to the homework problems.

Course language

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- will be English.
  - This applies to lectures, exercises, announcements, etc.
- Why?
  - Essentially all computer vision publications and books are written in English.
  - Knowing the original terms is crucial.
- If strongly preferred, you may contact the course staff in German.
  - English is encouraged though, because we may use your (anonymized) question to clarify points to the entire class.

Organization

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- Class type: IV4
- Lecture:
  - Wednesdays, 9:50 - 11:30, S3|05, room 074
  - We will cover the foundational aspects of each topic.
- Exercises, homework, etc.:
  - Wednesdays, 11:40 - 13:20, S3|05, room 074
  - irregularly
  - We will cover some practical aspects, and discuss the homework assignments.
  - Also: Time to work on your homework assignments.

Exam & Exercises

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- Exam:
  - Written (possibly oral) exam at the end of the semester.
  - Can be taken in English or German.
  - Exam date will be set and announced soon.
- Exercises:
  - Regular homework assignments; exercises will be graded.
  - Excercise points are part of your final grade (vorlesungsbleitende Prüfung)!
- Grading: 2/3 exam, 1/3 exercise

Homework assignments

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- Mostly programming assignments.
  - MATLAB, standard environment for scientific computing.
- Sometimes smaller pen and paper exercises
- The homework exercises are crucial for actually "digesting" the material from the lecture.
  - Hence your points count...
- Time commitment:
  - Solving the homework problems will require a substantial time commitment.
  - Keep in mind that 6CP equal a workload of approximately 180h / semester.

Collaboration policy

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- I do not tolerate plagiarism in any way!
- You may (and are encouraged to) discuss general class topics.
- But each handed in homework solution must be your own!
  - Any sources you used (other than provided by us) must be cited.
  - Details: TBA on the first homework assignment sheet.

- Questions? Problem cases?
  - Talk to us.

Readings

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- Good news: Additional book
  - Computer Vision: Models, Learning, and Inference by Simon Prince (Cambridge University Press, 2012)
  - Even better news: PDF online - http://www.computervisionmodels.com/
- Second book:
  - Computer Vision: Algorithms and Applications by Richard Szeliski (Springer, 2011)
  - Also good news: PDF available online - http://szeliski.org/Book
- Additional readings:
  - Papers and tutorials (on the web or course page)

How does it fit into your course plan?

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- Elective:
  - Part of Human Computer Systems (HCS) track.
- Related classes:
  - Human Computer Systems: prerequisite
  - Computer Vision I (Roth, WS): prerequisite
  - Maschinelles Lernen - Statistische Verfahren I (Peters, SS)
  - Maschinelles Lernen - Statistische Verfahren II (Roth, WS)
  - Bildverarbeitung (Sakas, SS)
- Theses and projects:
  - Topics in computer vision and machine learning.

Goal of today's lecture

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- Recap:
  - What is computer vision?
  - Why is it useful?
- CV2 - Probabilistic approaches to dense vision
  - Beyond sparse points
  - Beyond local processing
  - Focus on probabilistic approaches
- Tutorial example:
  - Stereo / disparity estimation
  - Optical flow

What is computer vision?

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[from Steve Seitz]

What does it mean to "see"?

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see [1] |sē|

verb (**sees** |sēz|, **seeing** |sē-i ng |; past **saw** |sô|; past part. **seen** |sēn|)

[trans.]
1 perceive with the eyes; discern visually *: in the distance she could see the blue sea* |
[intrans.] *Andrew couldn't see out of his left eye* figurative *I can't* ***see into*** *the future.*
• [with clause] be or become aware of something from observation or from a written or other visual source *: I see from your appraisal report that you have asked for training.*

...

[Oxford English dictionary, slide from Michael Black]

What does it mean to perceive"?

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perceive |pərˈsēv|

verb [trans.]
1 become aware or conscious of (something); come to realize or understand *: his mouth fell open as he perceived the truth* | [with clause] *he was quick to perceive that there was little future in such arguments.*
• become aware of (something) by the use of one of the senses, esp. that of sight *: he perceived the faintest of flushes creeping up her neck.*
2 interpret or look on (someone or something) in a particular way; regard as *: if Guy does not* ***perceive*** *himself* ***as*** *disabled, nobody else should* | [trans.] *some geographers perceive hydrology to be a separate field of scientific inquiry.*

[Oxford English dictionary, slide from Michael Black]

Computer Vision

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- What is computer vision (or machine vision)?
  - Developing computational models and algorithms to interpret digital images / understand the visual world we live in.

[from Steve Seitz]

Computer Vision

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- What is computer vision (or machine vision)?
  - Developing computational models and algorithms to interpret digital images / understand the visual world we live in.
- Is that important?
- What can we (already) do with it?

Face detection

e.g. Canon [powershot.com], etc.

Human pose estimation

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Microsoft Kinect

[www.xbox.com/kinect]

Earth viewers

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Google Street View

[www.google.com]

[www.mobile3dcity.com]

Photosynth

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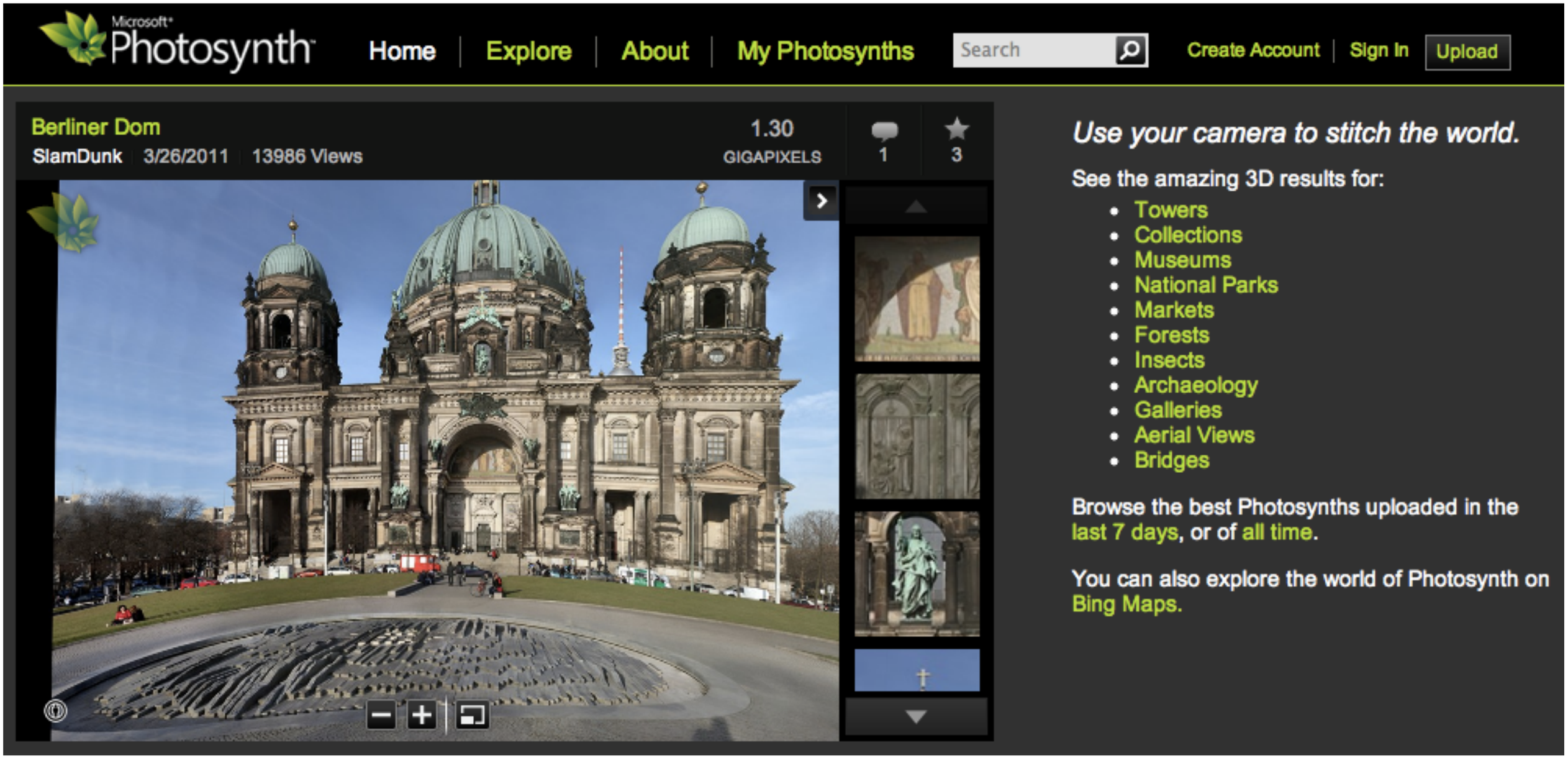

[photosynth.net]

Optical character recognition (OCR)

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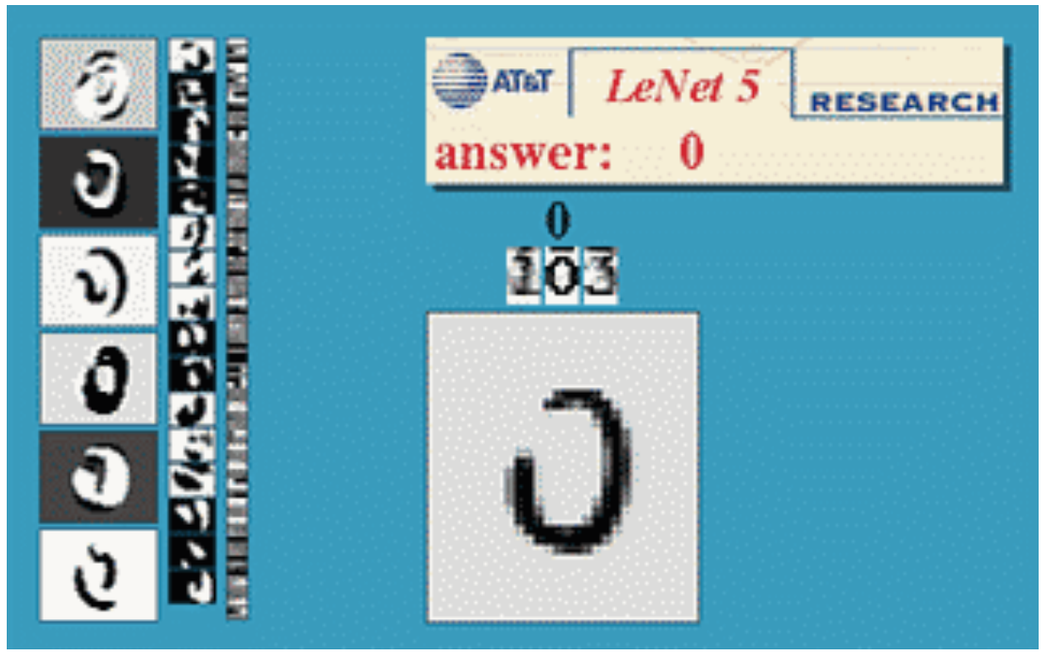
- Convert scanned documents to text



Digit recognition, AT&T labs
[www.research.att.com/~yann/]

License plate readers
[en.wikipedia.org/wiki/Automatic_number_plate_recognition]

[from Steve Seitz]

Traffic sign recognition

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Opel

VDO

Special effects: Shape capture

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The Matrix movies, ...

[from Steve Seitz]

Special effects: Motion capture

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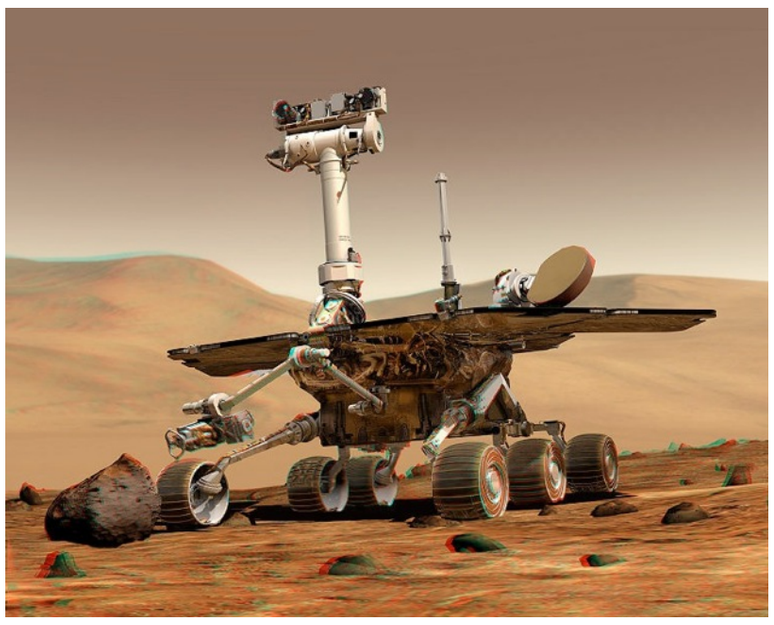
Pirates of the Carribean, Industrial Light and Magic [from Steve Seitz]

Sports

3D soccer analysis

[www.kicker.de]

Vision in space



NASA's mars exploration rover Spirit

[en.wikipedia.org/wiki/Spirit_rover]

[from Steve Seitz]

Robotics

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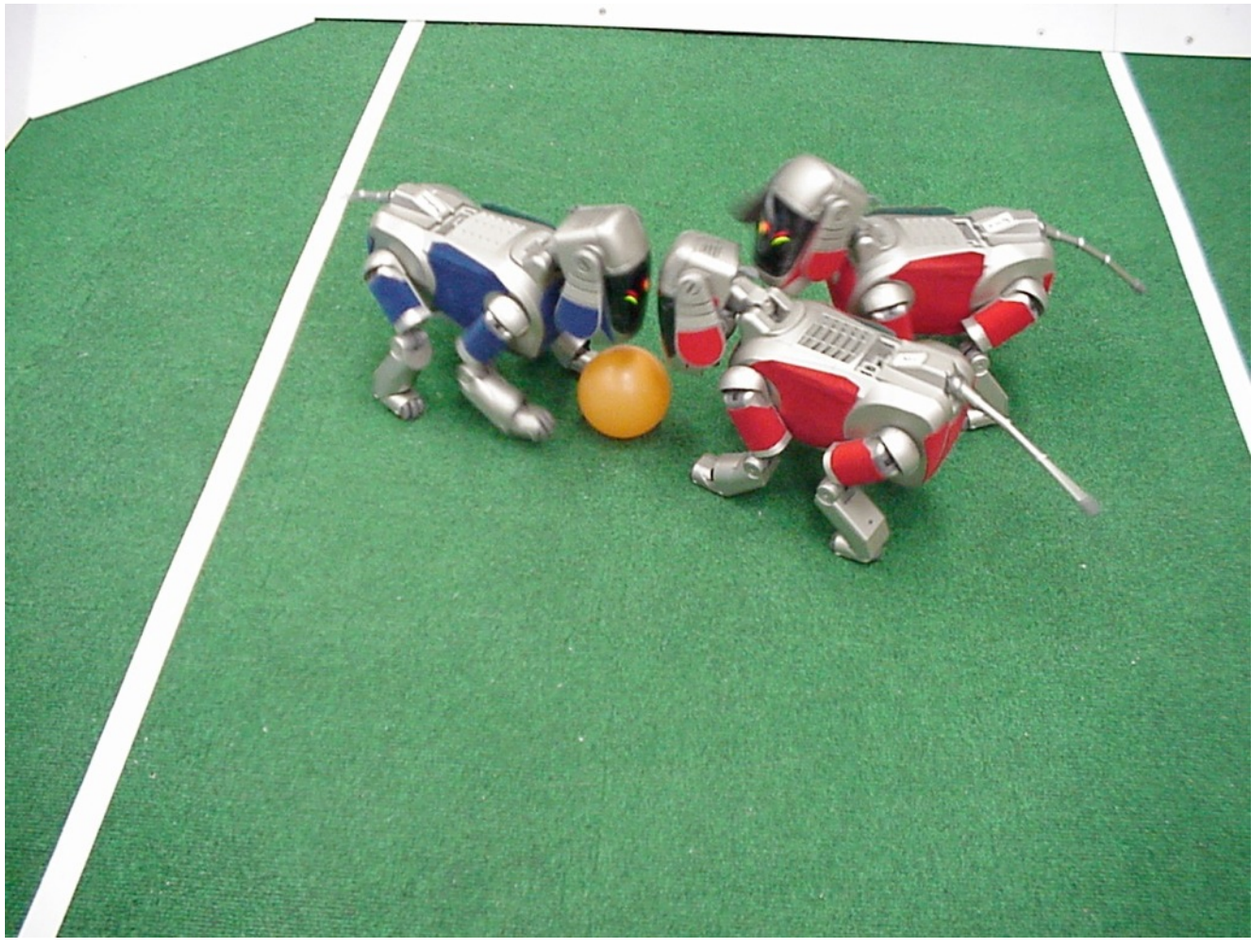

Robocup

[www.robocup.org]

Darmstadt Dribblers [FG SIM]

Medical imaging

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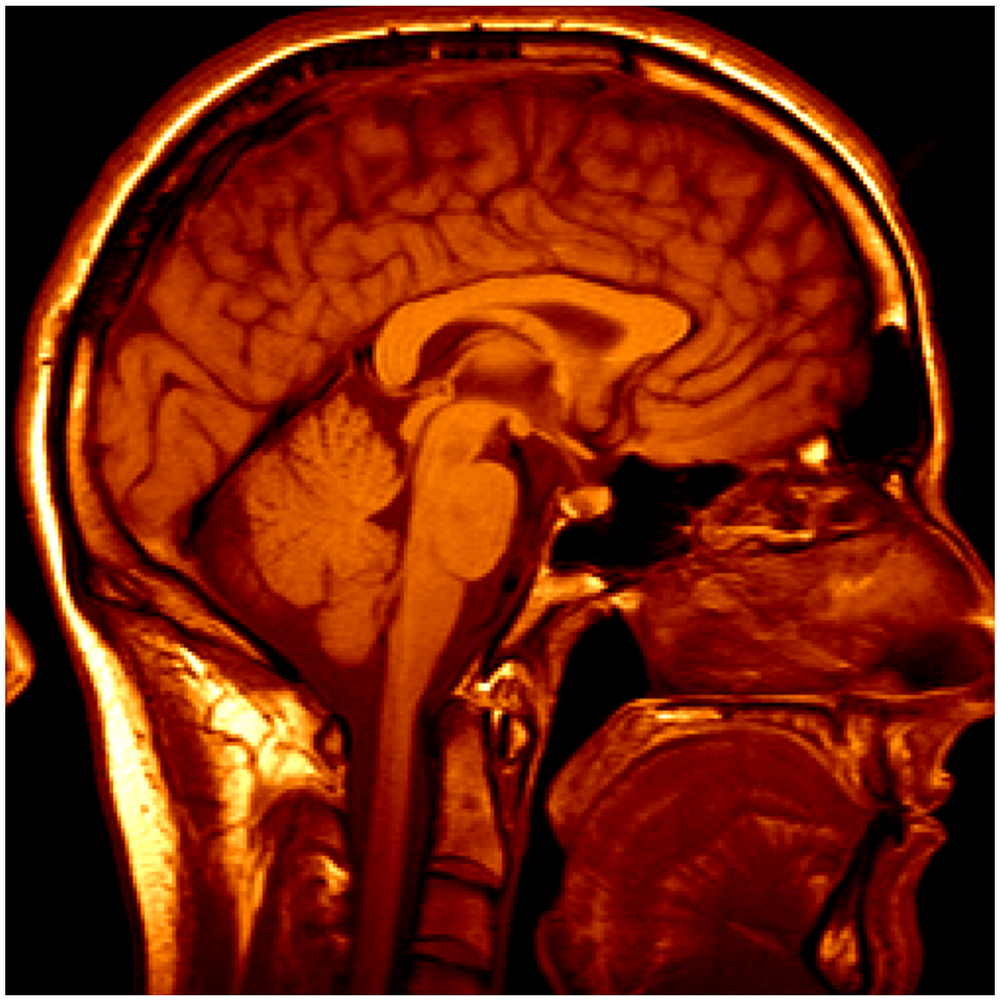

3D imaging
MRI, CT

Image guided surgery
Grimson et al., MIT

[from Steve Seitz]

Computer Vision

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- We need a formal model that describes our problem *as well as* an algorithm that realizes (i.e. implements) it.
  - Neither the model alone, nor the algorithm alone suffices (in the long run).
  - Both mathematical and computational.

- What properties / cues of the visual world can we exploit or measure?
- What general (prior) knowledge of the world (not necessarily visual) should we exploit?

[adapted from Michael Black]

Ambiguity of Data

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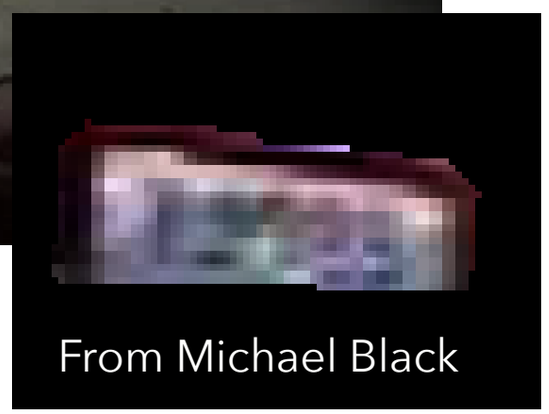
- Our image data is not only too little to fully recover and understand the “state of the visible world”.
- It may even be of poor quality:
  - Low resolution
  - (Sensor) noise
  - Etc.


Courtesy Criterion Collection


From Michael Black

- Our image data is always ambiguous.

Computer Vision

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- We want to devise computer algorithms to understand the visual world much like we do.
- This means:
  - We have to use a lot of different cues...
  - We have to deal with ambiguity...
  - We have to exploit what is a plausible and meaningful interpretation...
  - ... in order to extract information about the 3D visual world from a small amount of data.
- CV is an inverse problem.

What have we learned in CV1?

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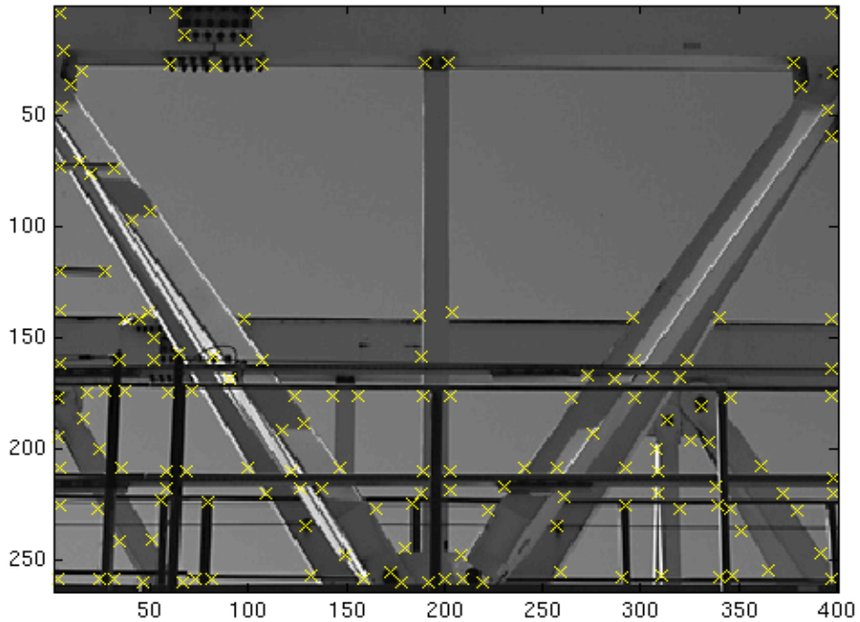
- Fundamentals of cameras and digital imaging
- Filtering and pyramid representations
- Template-based recognition
  - PCA, eigenfaces...
- Object recognition with histograms
  - ... with sparse points (BoW)
- Motion estimation
- Epipolar geometry
- Disparity estimation
- Segmentation



focus on sparse points or local methods

From CV1 to CV2

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- Moving from
  - sparse to **dense**
  - local to **global**
- But why?
  - Haven't we solved these problems already?
- Two case studies:
  - Stereo
  - Optical flow

Stereo

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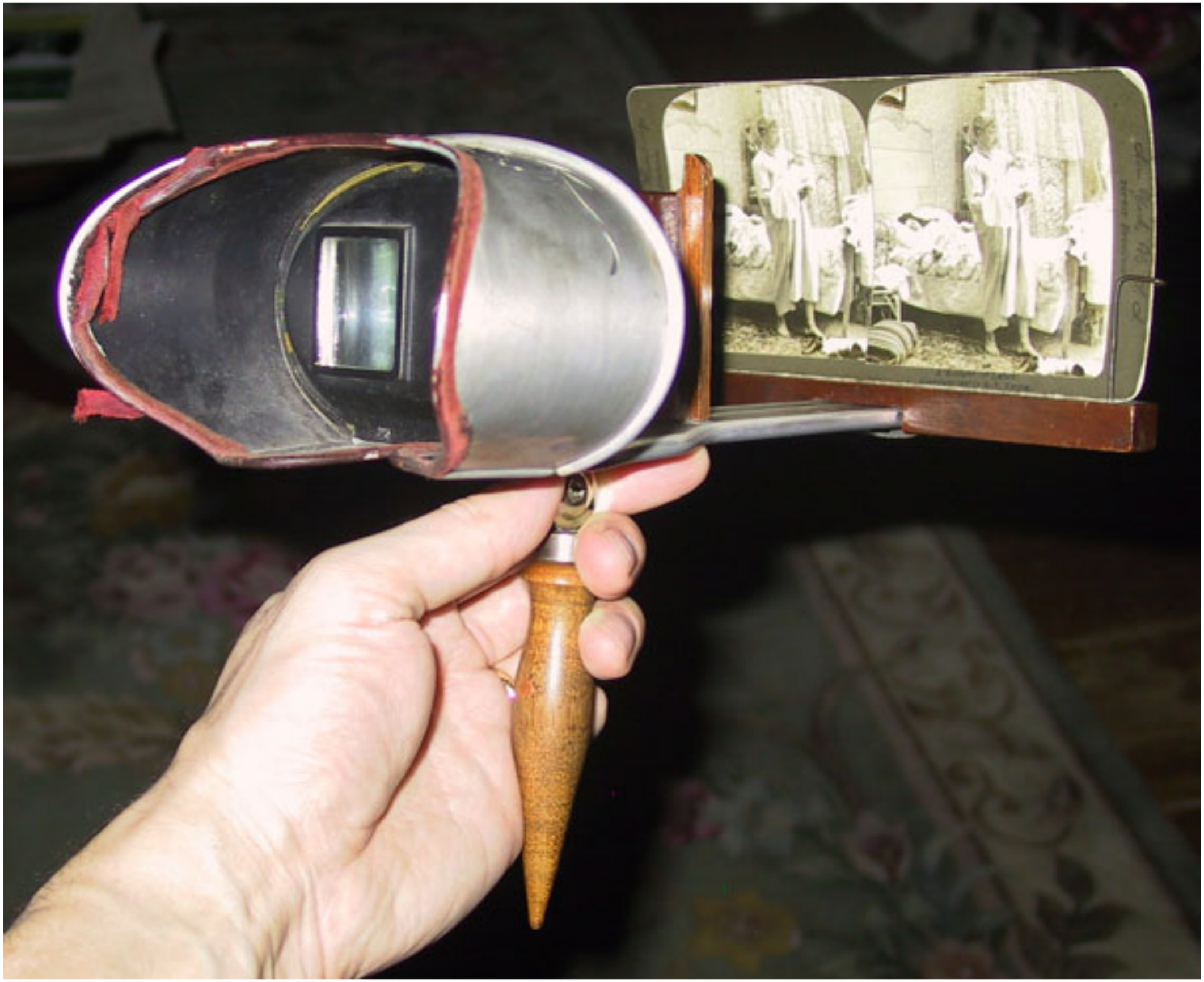

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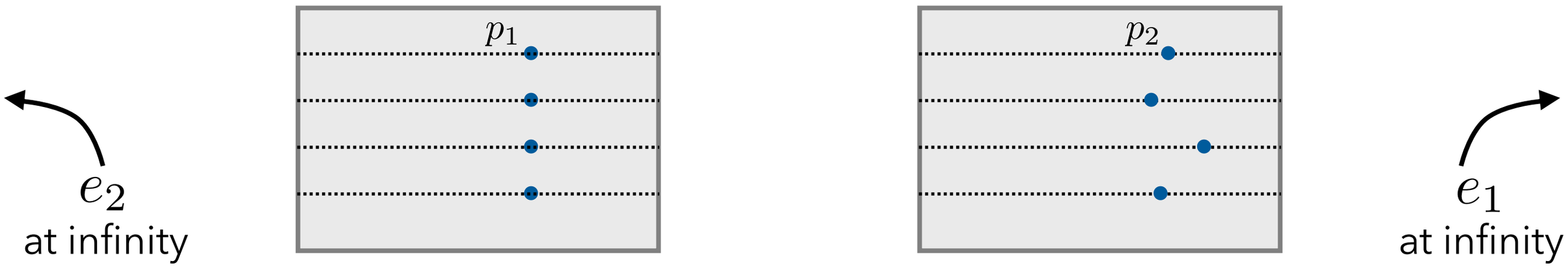
Binocular Stereo



- Special case of epipolar geometry for stereo cameras with a standard binocular setup:
  - Epipoles are at infinity.
  - Epipolar lines are parallel.
  - Points correspond along the scanlines of the image.

Binocular Stereo

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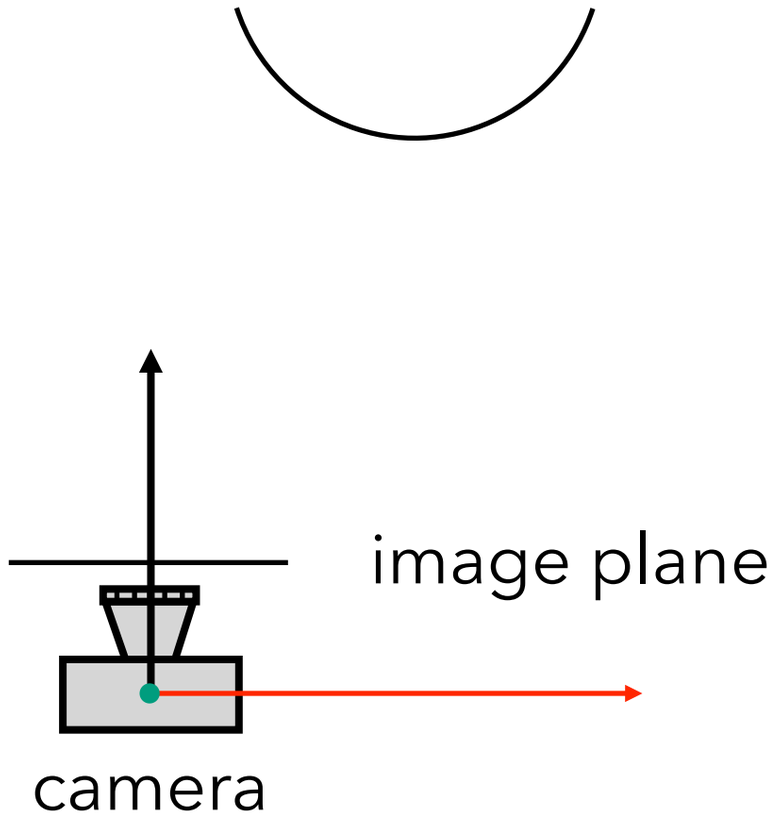
Left



Binocular Stereo

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Left

Right

Binocular Stereo

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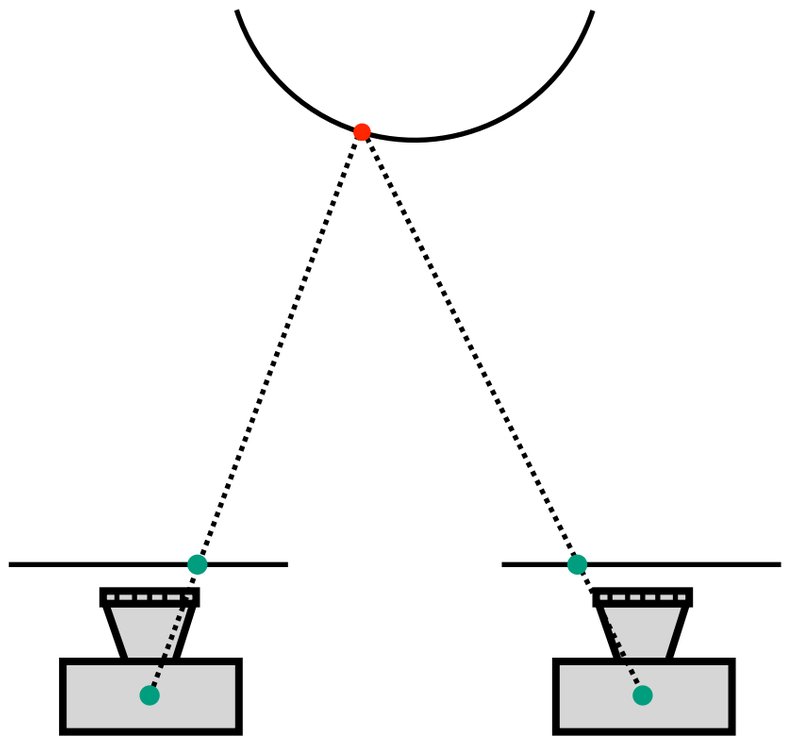

Left

Right

Binocular Stereo

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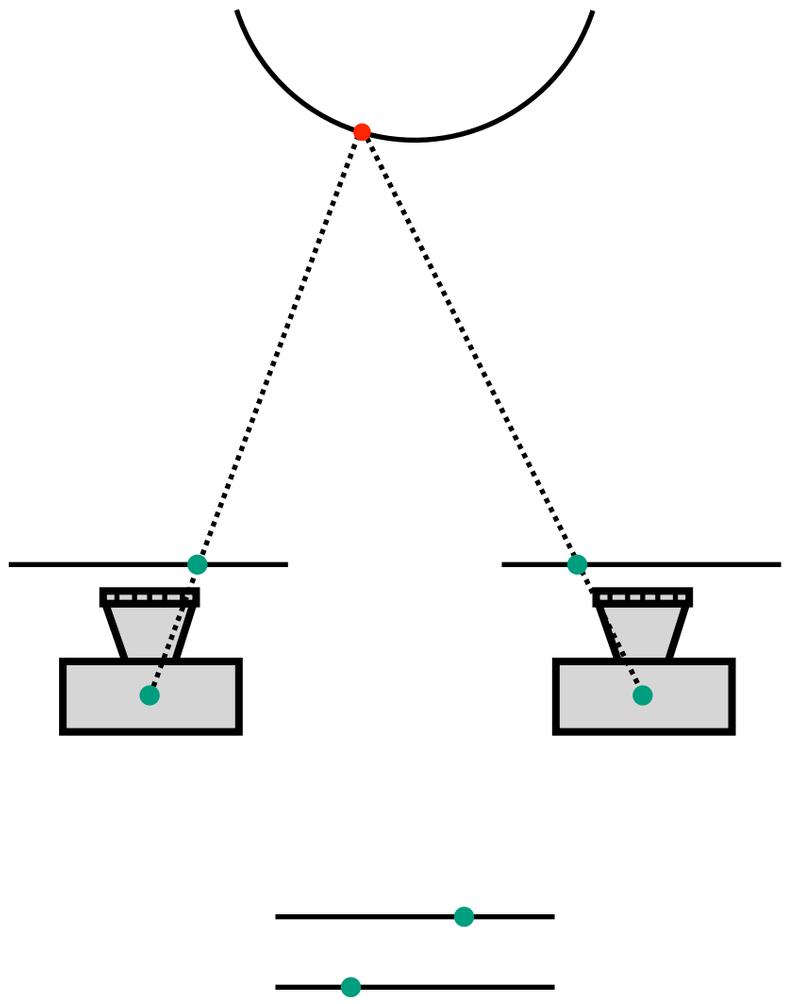

Left

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Binocular Stereo

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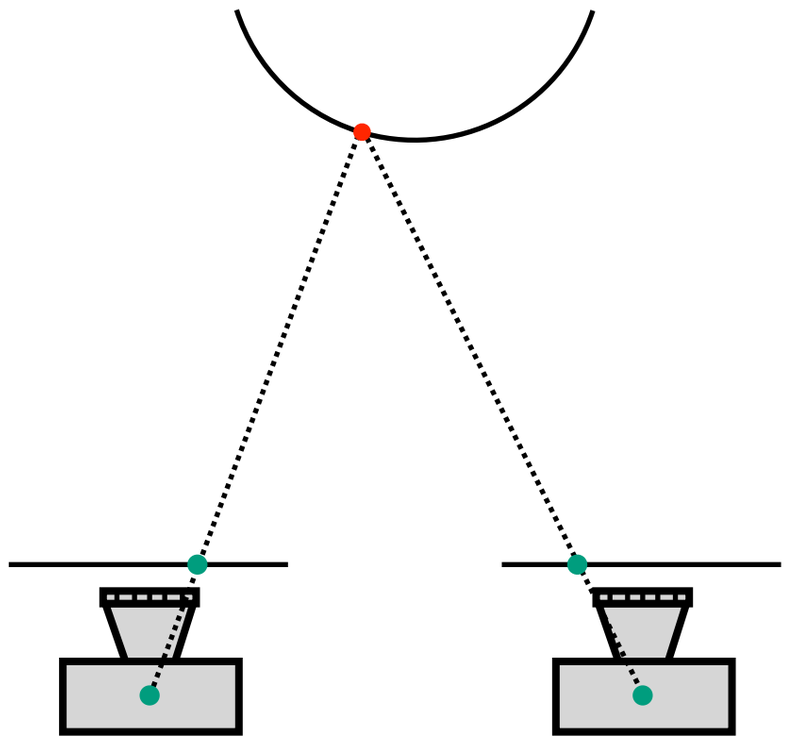
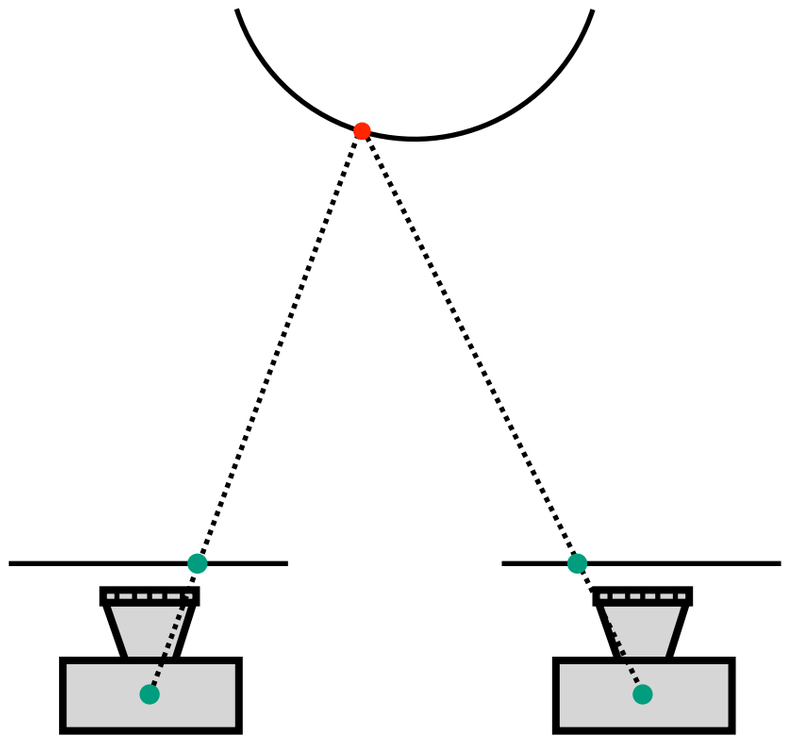


Left

Right

binocular disparity

Binocular Stereo



From known geometry of the cameras and estimated disparity, recover depth in the scene

Left

Right

binocular disparity

Triangulation

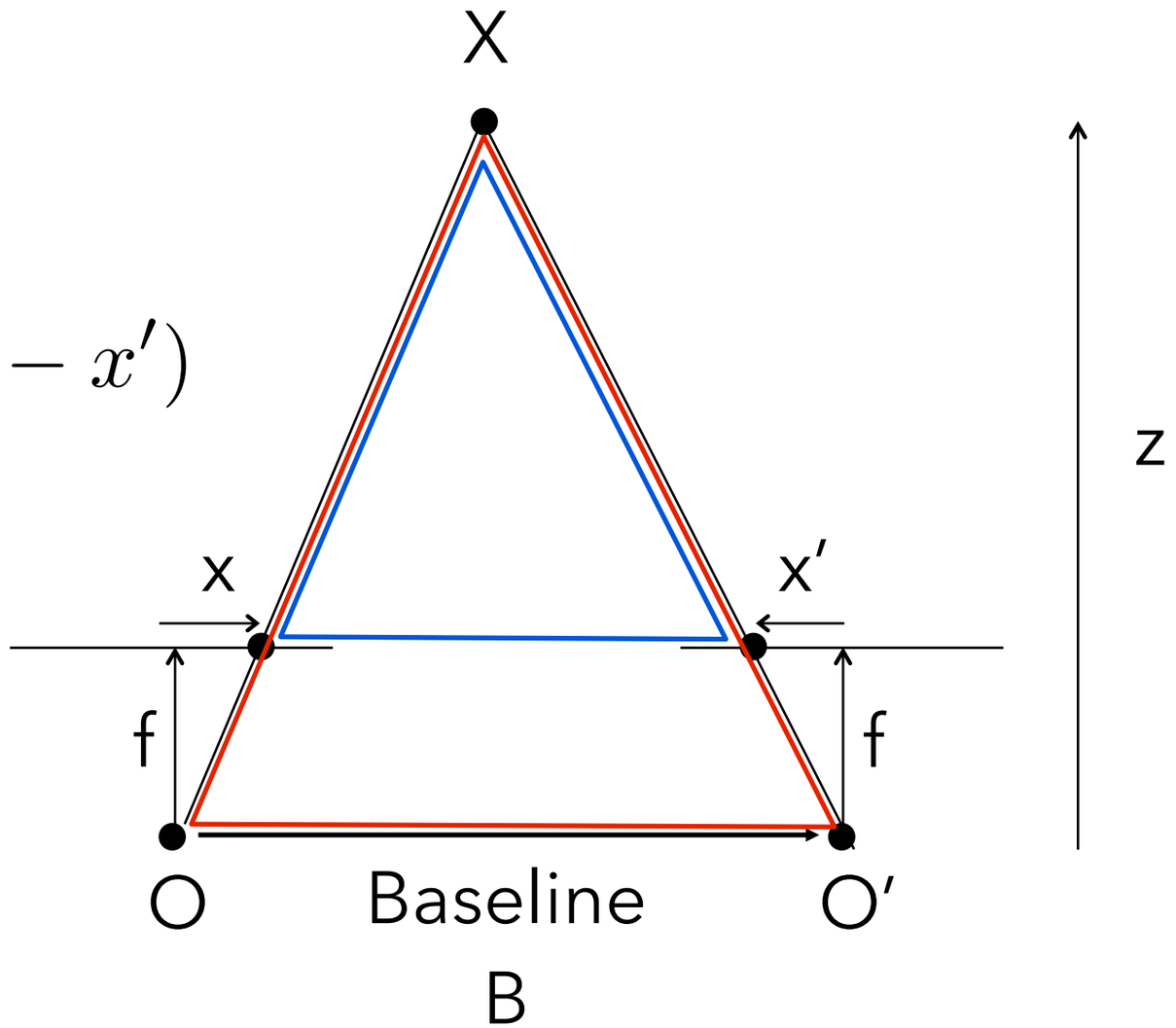
$$\frac{Z-f}{B-(x-x')} = \frac{Z}{B}$$

$$B \cdot Z - B \cdot f = B \cdot Z - Z \cdot (x-x')$$

$$Z = \frac{B \cdot f}{x-x'}$$

$$d = x - x' = \frac{B \cdot f}{Z}$$

disparity



- Parallel image planes: disparity from equal triangles

Binocular Disparity

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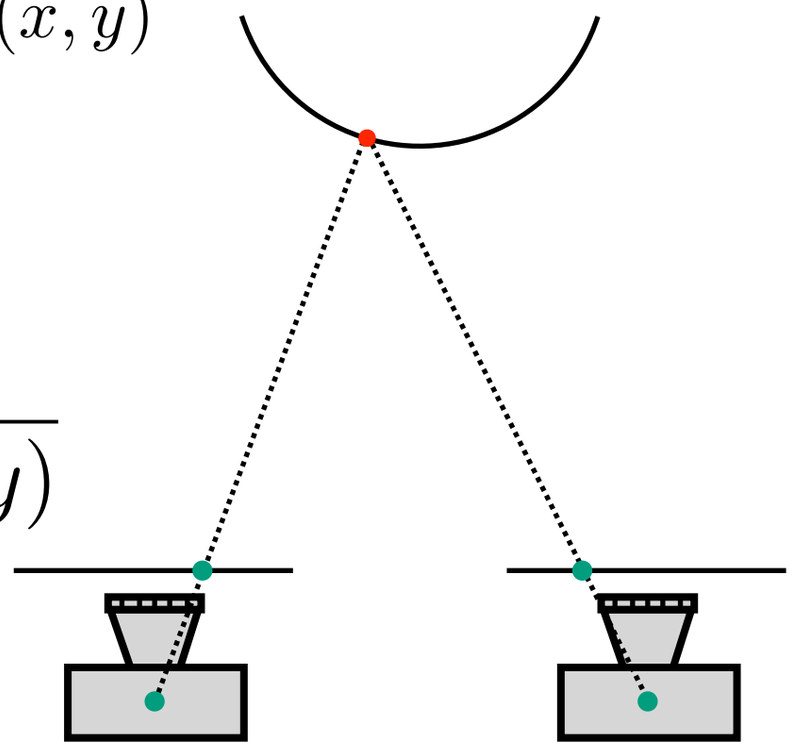
$Z(x,y)$ is depth at pixel (x,y)

$d(x,y)$ is disparity

Estimate:

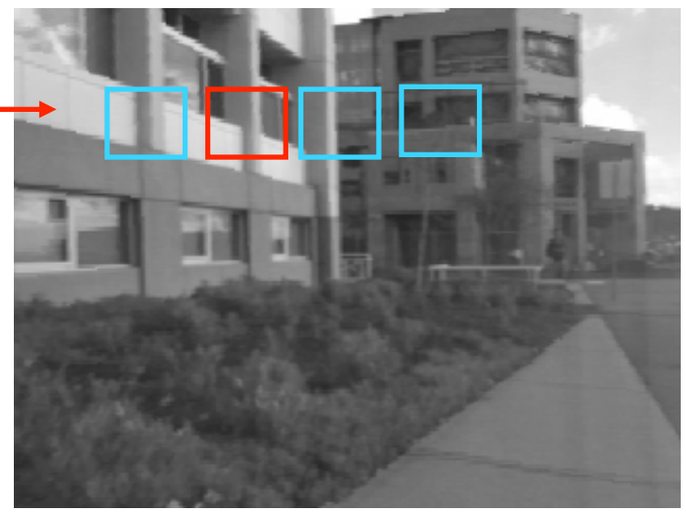
$$Z(x,y) = \frac{fB}{d(x,y)}$$



Left

Search for best match

Right



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Stereo Correspondence

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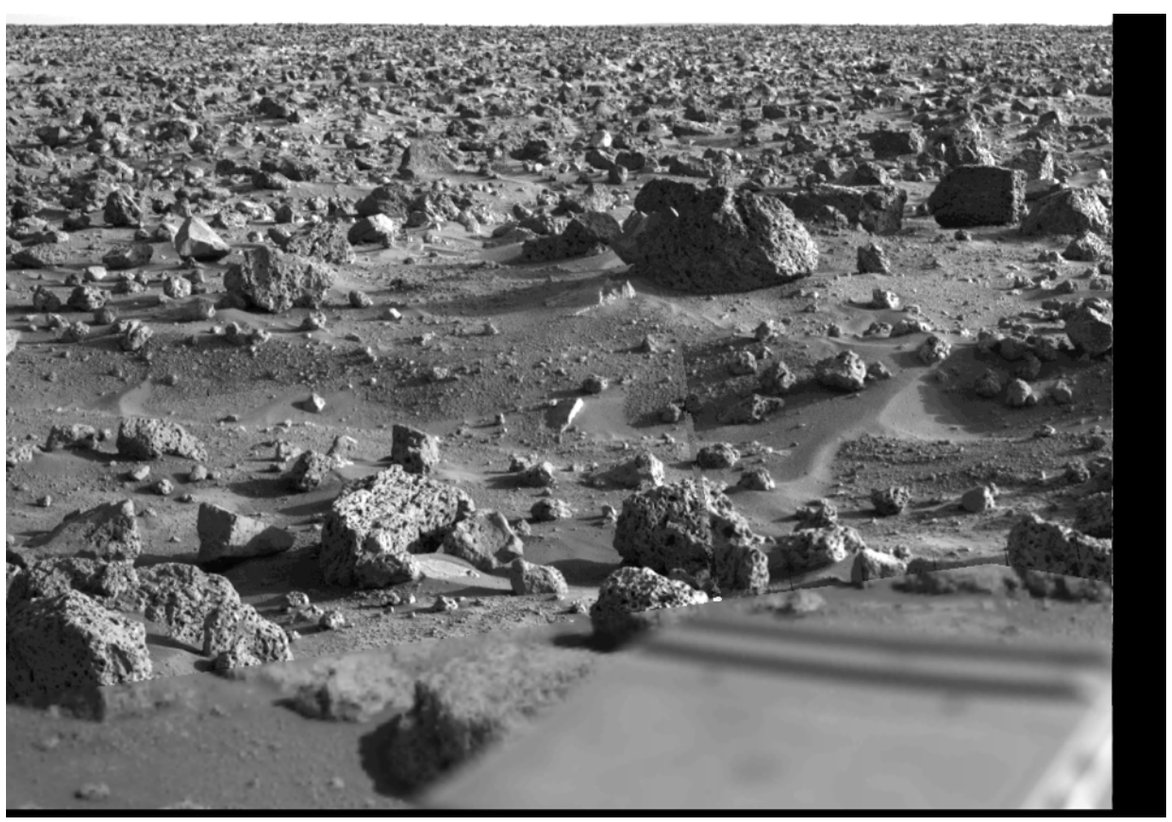
- Search over disparity to find correspondences
- Range of disparities to search over can change dramatically within a single image pair.



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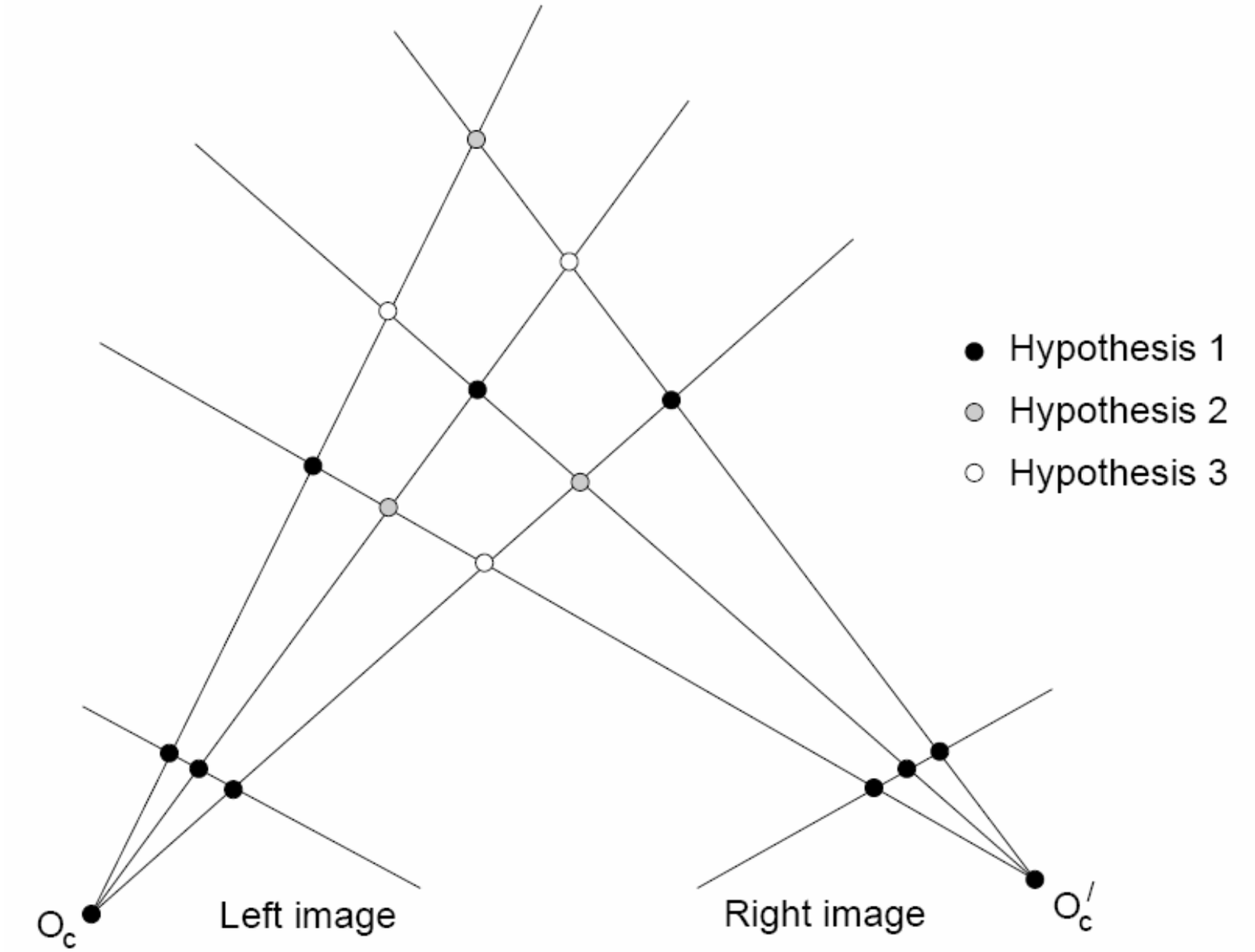
Correspondence problem



Even when constrained to 1D, there are multiple matching hypotheses - which one is correct?

Correspondence problem

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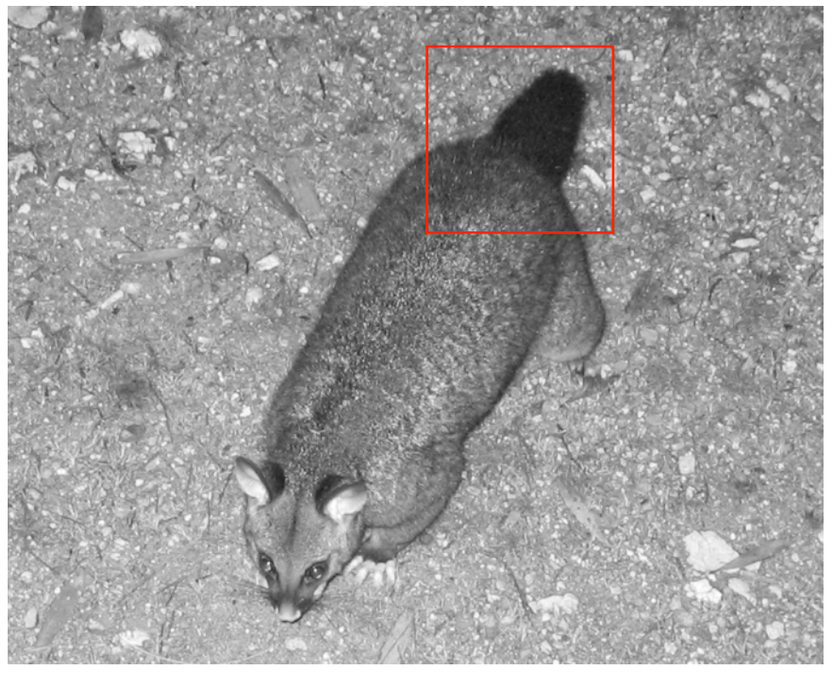
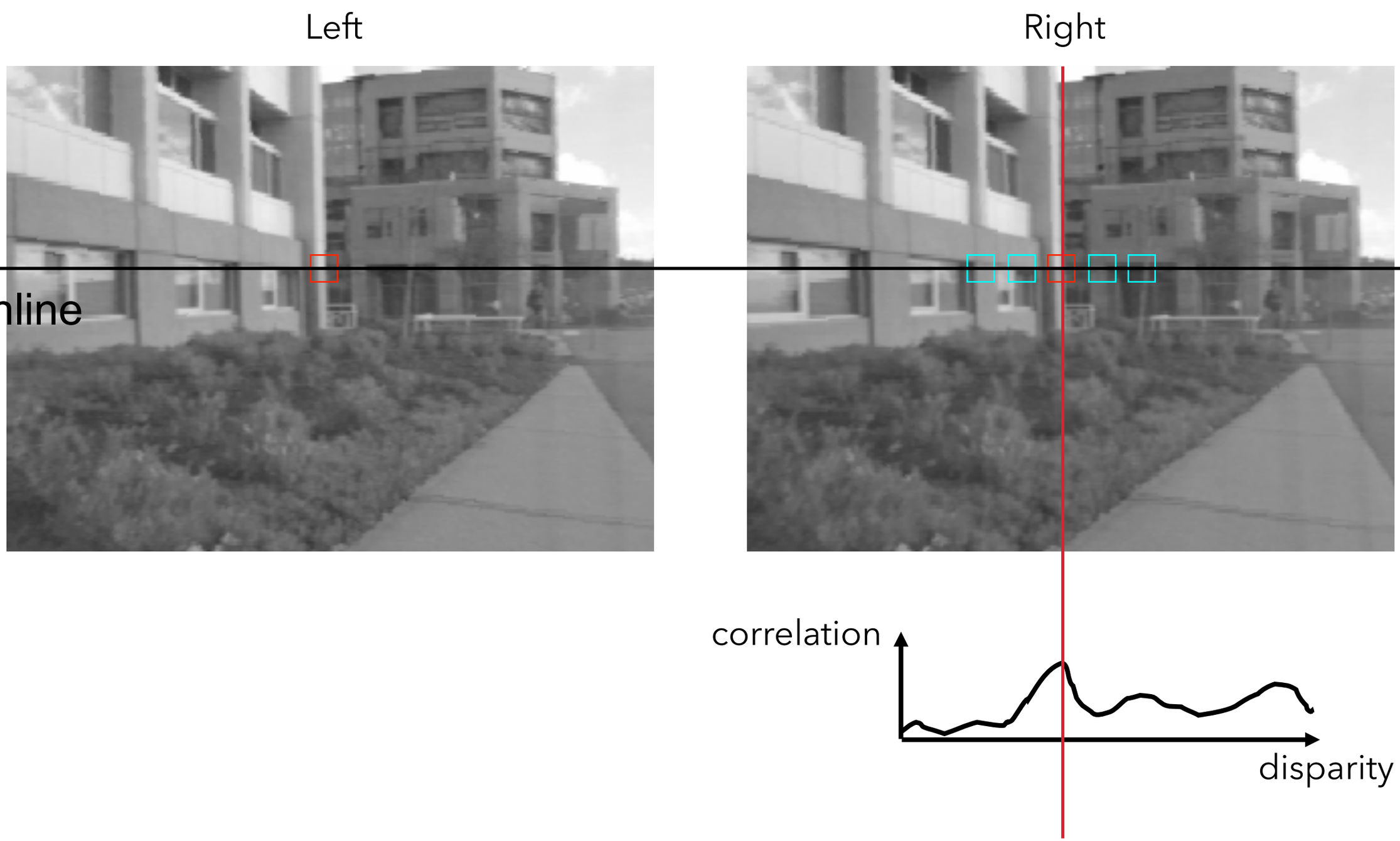
- Matching with narrow baseline
  - What are two “similar pixels”?
  - An ill-posed question, a single intensity sample does not reveal the local image structure
  - Measure similarity of the surrounding region
  - **Area-based similarity measures**





Correspondence Using Correlation



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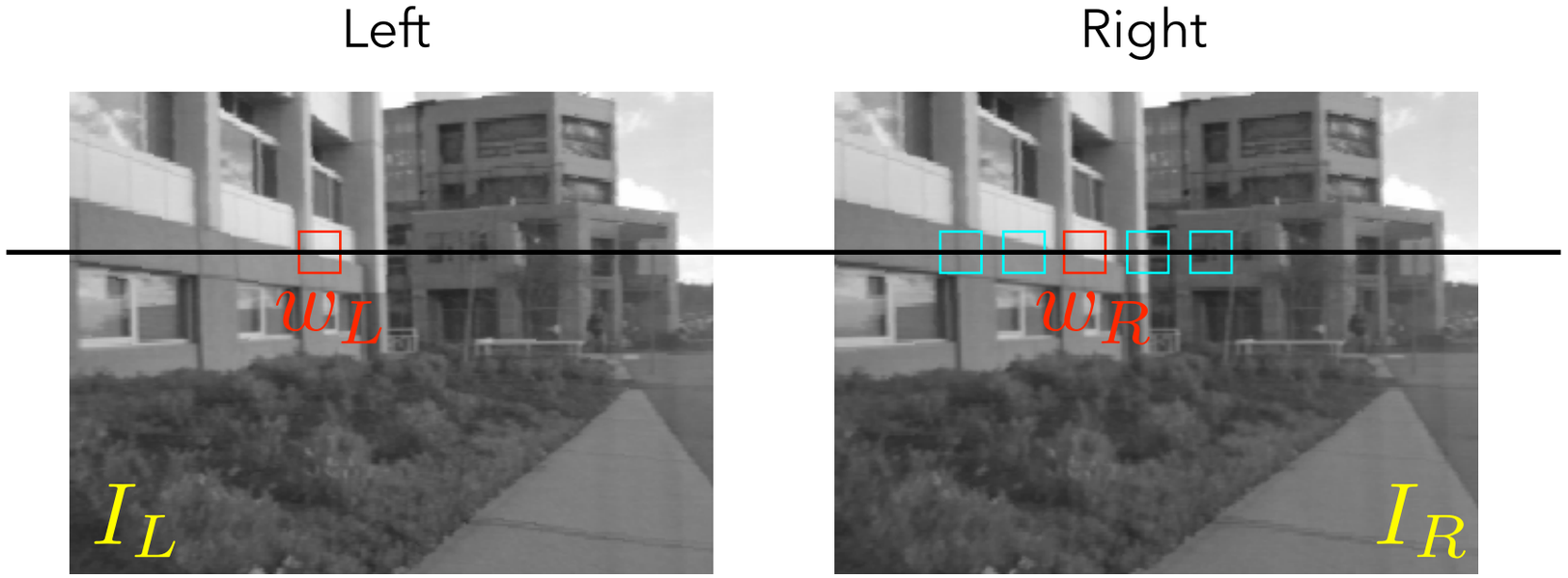
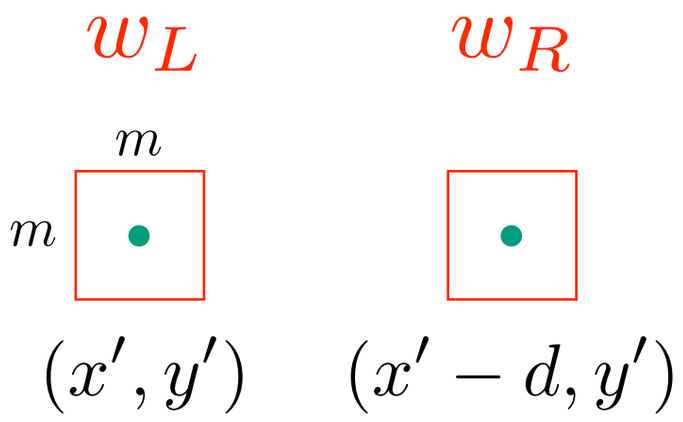
Normalized Correlation



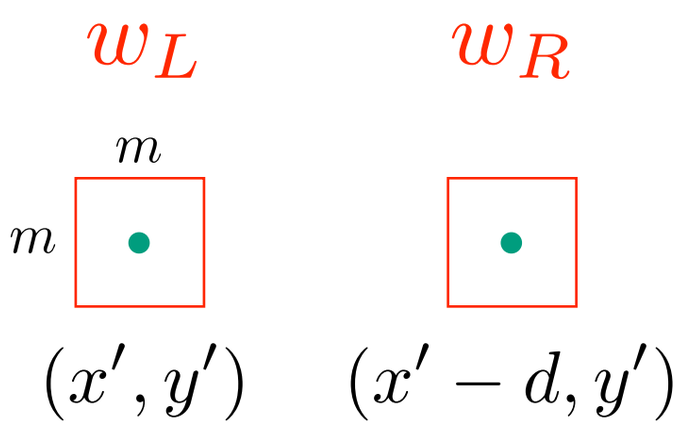


- w_L and w_R are corresponding $m \times m$ windows of pixels. We also write them as vectors $\mathbf{w}_L$ and $\mathbf{w}_R$.
- The normalized correlation computes the cosine of the angle between the patches:

$$\mathrm{NC}(x, y, d) = \frac{(\mathbf{w}_L(x, y) - \bar{\mathbf{w}}_L(x, y))^{\mathrm{T}} (\mathbf{w}_R(x - d, y) - \bar{\mathbf{w}}_R(x - d, y))}{|\mathbf{w}_L(x, y) - \bar{\mathbf{w}}_L(x, y)| \, |\mathbf{w}_R(x - d, y) - \bar{\mathbf{w}}_R(x - d, y)|}$$

patch mean

Even simpler: Sum of Squared (Pixel) Differences



- w_L and w_R are corresponding $m \times m$ windows of pixels.
- The SSD cost measures the intensity difference as a function of disparity:

$$\mathrm{SSD}_R(x, y, d) = \sum_{(x',y') \in w_L(x,y)} (I_L(x', y') - I_R(x' - d, y'))^2$$

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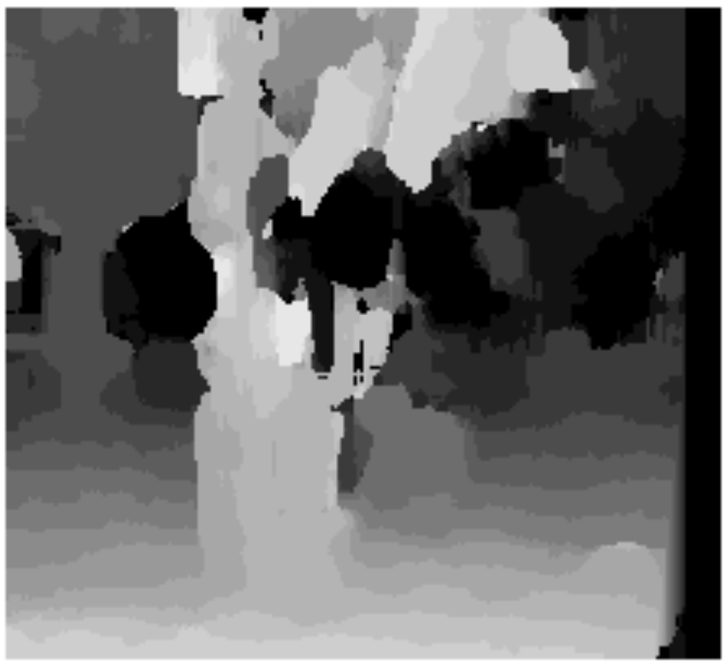
Influence of window size

$m = 3$



$m = 20$

- Challenges and Problems:
  - How do we choose the right window size m?
  - Mismatches often lead to relatively poor results quality.

Preview: Stereo results

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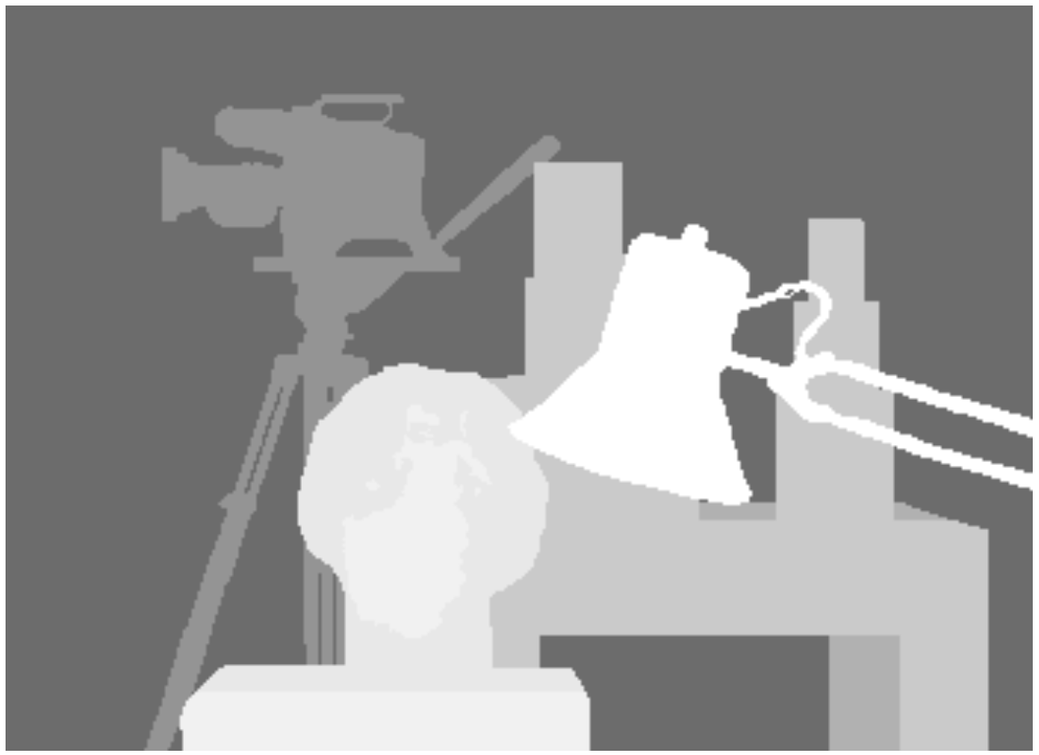
- Data from University of Tsukuba:

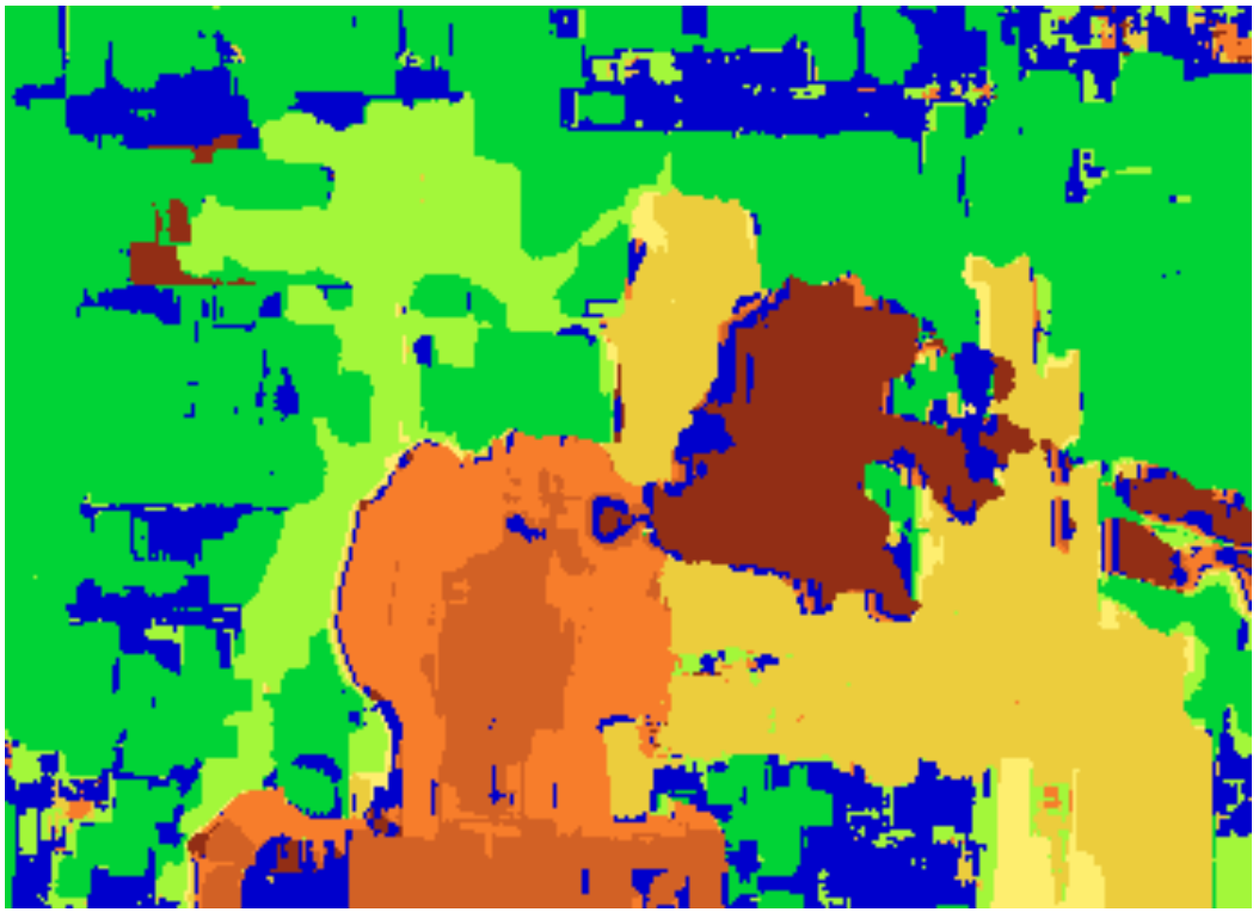
Scene



Ground truth

[Seitz]

Results with window correlation



Window-based matching
(best window size)

Ground truth

[Seitz]

How can we improve window-based matching?

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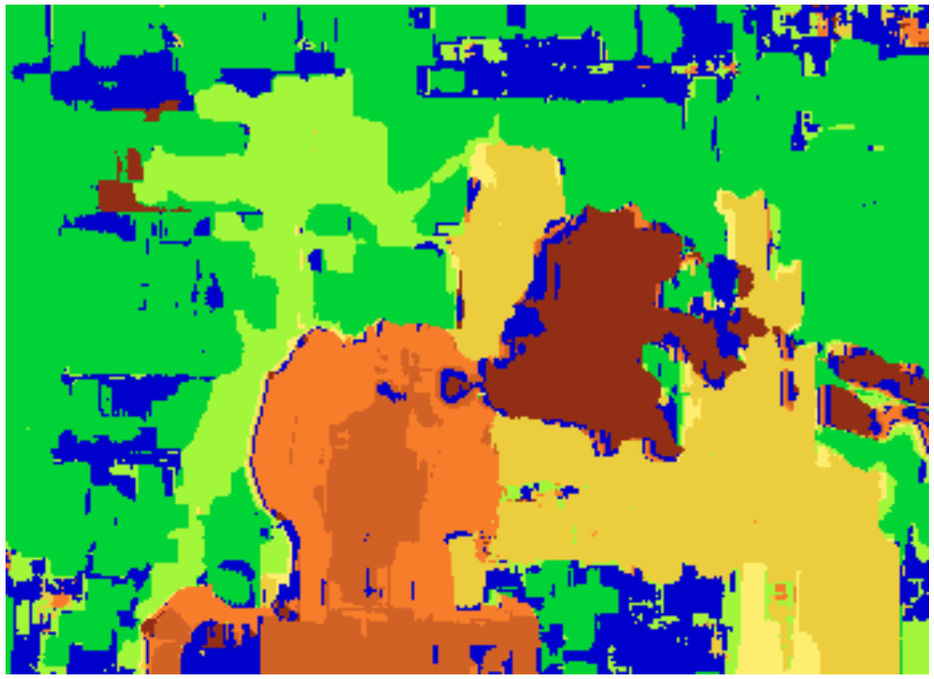
- The similarity constraint is local
  - each reference window is matched independently
  - other points do not influence the result



How can we improve window-based matching?

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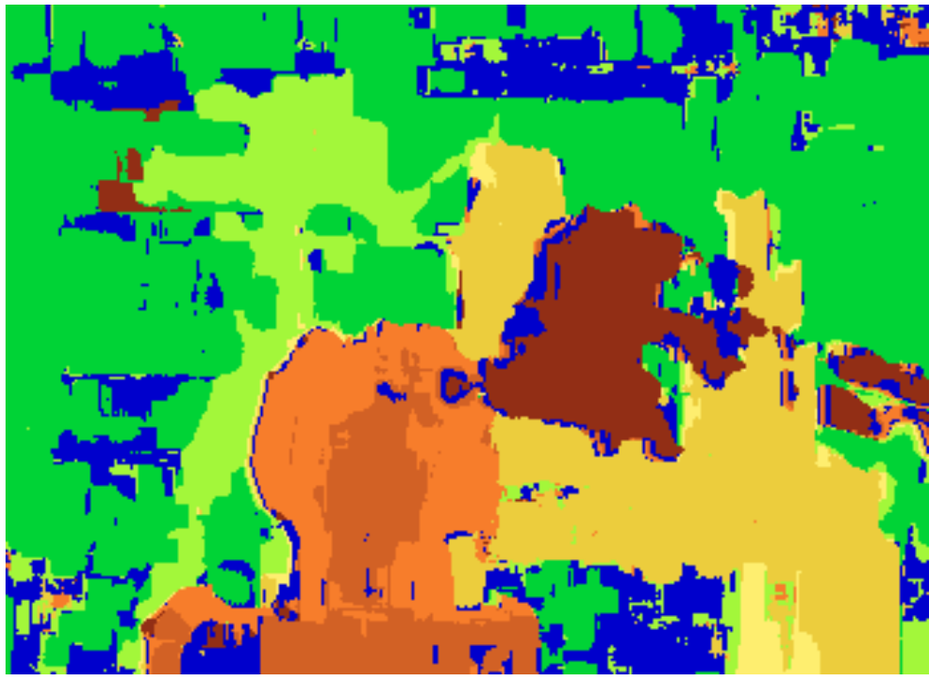
- The similarity constraint is local
  - each reference window is matched independently
  - other points do not influence the result
- Need to enforce non-local correspondence constraints



Slide by Lana Lazebnik

Where do we go from here?

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- How can we impose regularity constraints that impose global consistency?
  - This is also called **regularization**.
- Goals:
  - We want to go beyond matching windows.
  - We want consistency within and between scanlines.
  - We want a model of consistency that is well supported by the properties of the real world, e.g. by real scene depth or real motion.
  - We want a model that is computationally manageable.
  - We would like to find a model of consistency that does not only work for stereo or flow, but also for other applications.

What is consistency?

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- Before we can do anything, we need to ask ourselves what it means to have spatial consistency or regularity.
- Let's look at some data to get inspiration:

Range image - Scene depth from a range scanner

Range Scanning

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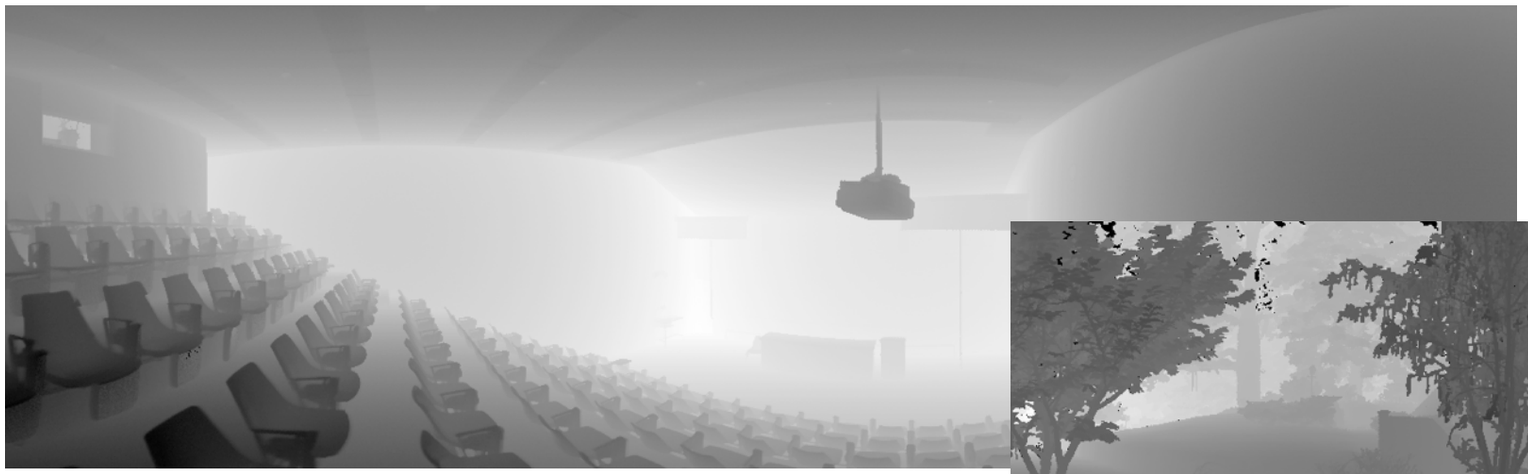
- This image was captured using a laser range finder.
  - Measures the distance to each point in the scene.
  - Based on the time of flight of a laser beam.
  - Quite accurate: ~15mm
  - Angular resolution: 0.005°
- Brown Range Image Database:
  - David Mumford and (former) students

From Riegl



[Lee, Huang, & Mumford]

What can we conclude from this data?

- It helps us see more clearly what we know from everyday life:
  - The depth of nearby points in the scene is (almost) the same.
  - But sometimes, there are depth discontinuities, for example at object boundaries.

What can we conclude from this data?

- In other terms:
  - We (as humans) have **a-priori knowledge** about how 3D scenes typically look like, even if we have never seen the particular scene in question before.
- How do we exploit this a-priori knowledge for computer vision?

Vision as Probabilistic Inference

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- In the introduction we discussed that:
  - Many vision problems are underconstrained and require prior knowledge to be solved (as is the case here).
  - We almost always have to deal with uncertain ("noisy") data.
- Both of these are key motivations for using **probabilistic approaches** to computer vision:
  - We regard both the measurement and the interpretation as uncertain (Bayesian approach).
  - We model the problem using probabilities (or prob. densities).
  - We obtain the solution using methods of probabilistic inference.
- What does all this mean?

Stereo using Probabilistic Methods

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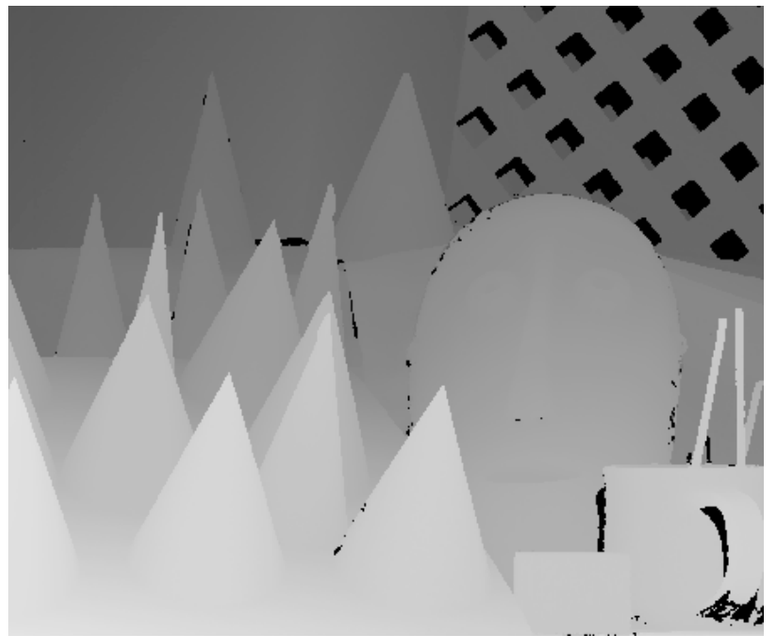
Uncertain image measurements



Uncertain state of the world

We're given

Want to know

Stereo using Probabilistic Methods

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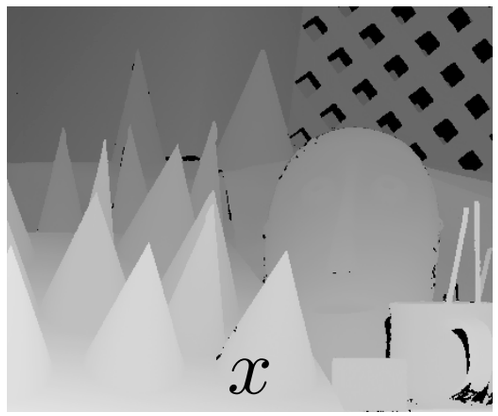
Uncertain image measurements



Uncertain state of the world

- Model using posterior distribution: $p(\text{state}|\text{images})$
  - Describe the probability of the state of the world given the image measurements.
- How do we find the “best” state of the world?
  - Using probabilistic inference, e.g. we maximize w.r.t. state x

Modeling the Posterior

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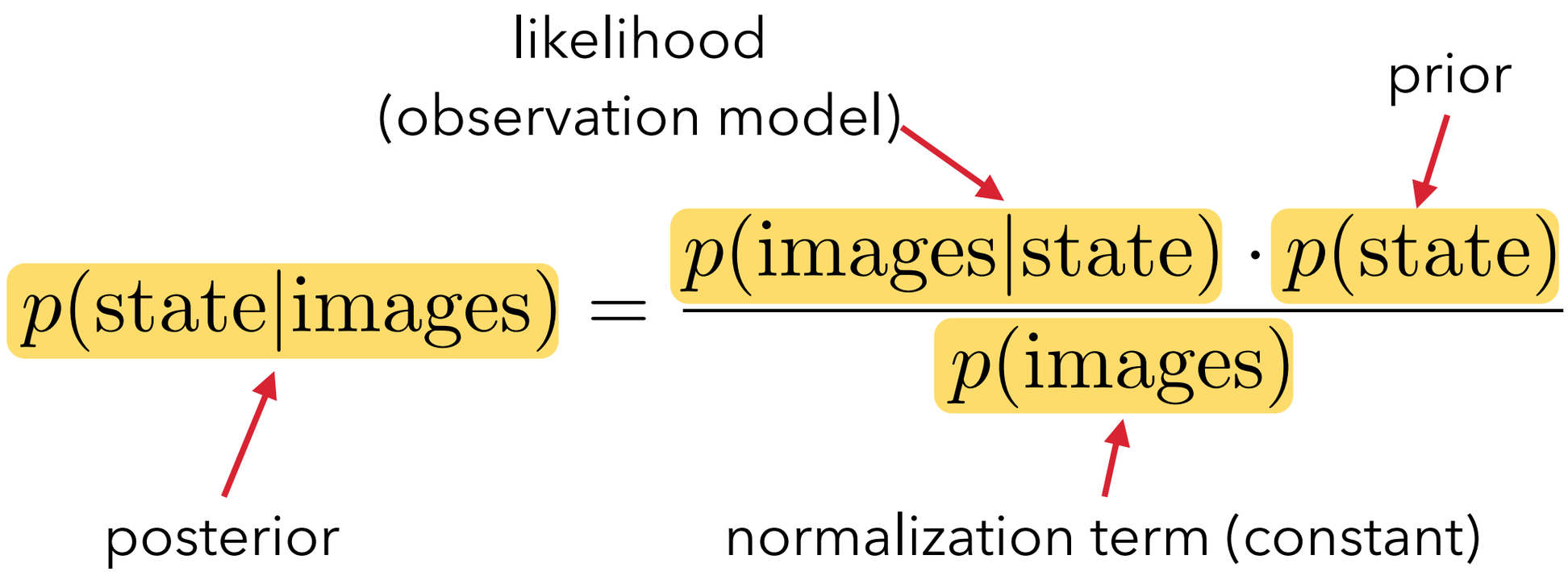
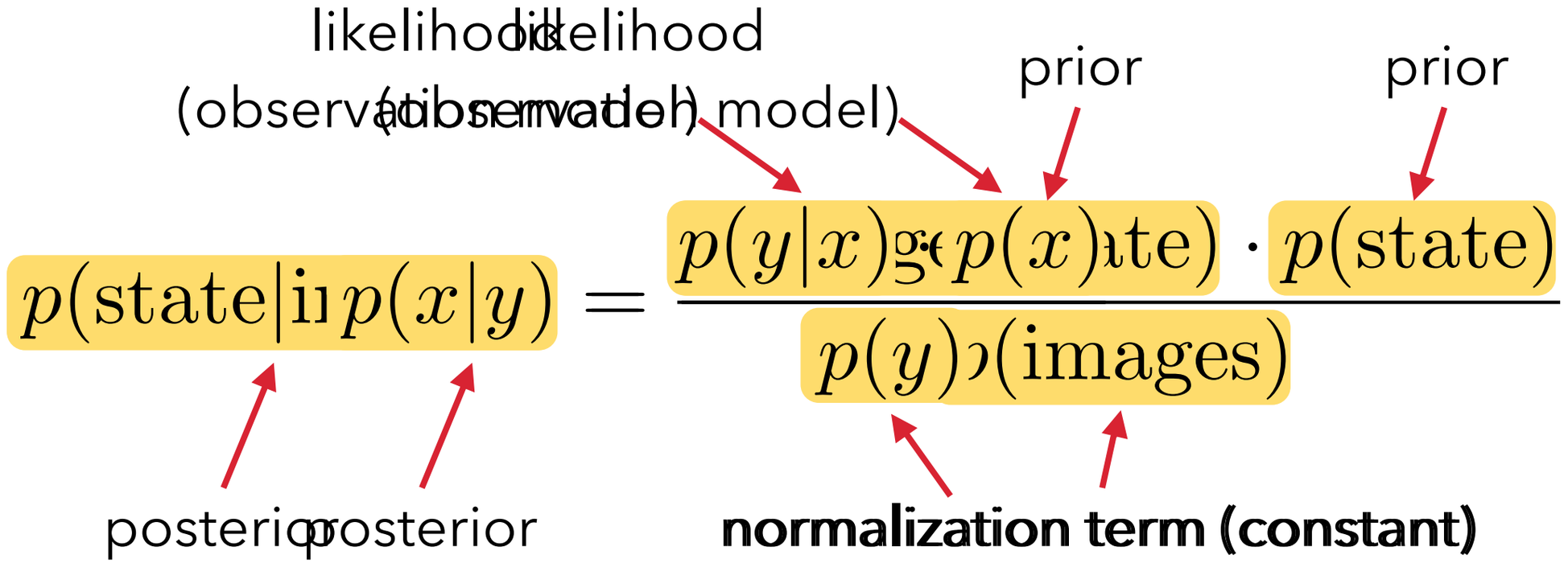
- How do we model the posterior?
  - This can be done directly (discriminative approaches), but we will not do this now as it is more difficult.
- Instead, we simplify the modeling problem by applying Bayes' rule (generative approach):



Modeling the Posterior



- The likelihood $p(y|x)$is an observation model that describes how we obtained the image measurements, given a particular state of the world.
- The prior $p(x)$models our a-priori assumptions about the world, or the state of the world.
- The normalization term $p(y)$can often be ignored, because it only depends on the image measurements, which are given to us.

Three problems

- How do we model the likelihood $p(y|x)$?
  - Stereo, flow, image restoration, etc.

- How do we model the prior $p(x)$?
  - Again, many applications
  - disparity, motion, natural images, image segments, etc.

- Given the posterior, how do we compute a solution?
  - What is the right objective?
  - What are good algorithms?

Optical Flow

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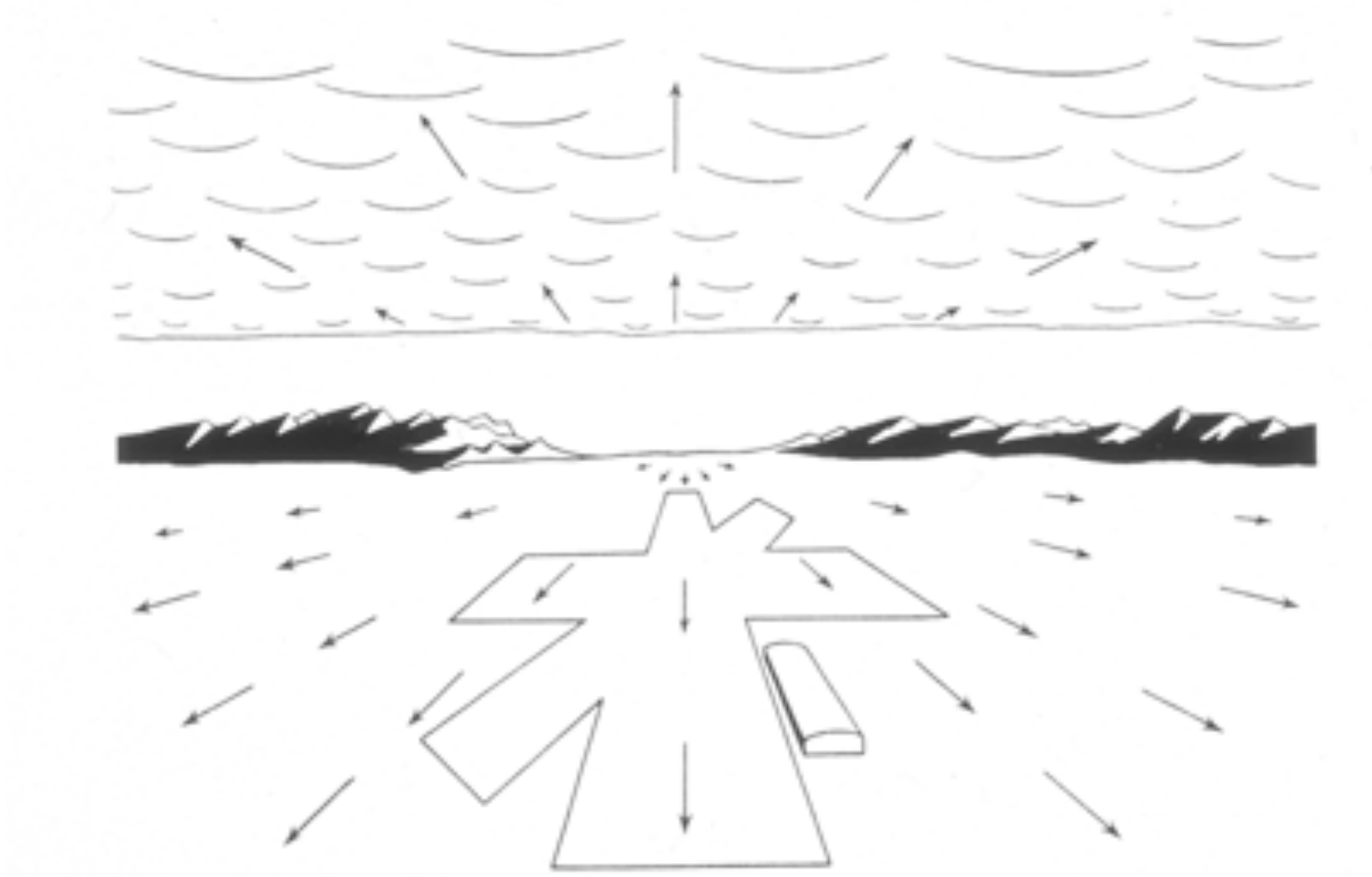
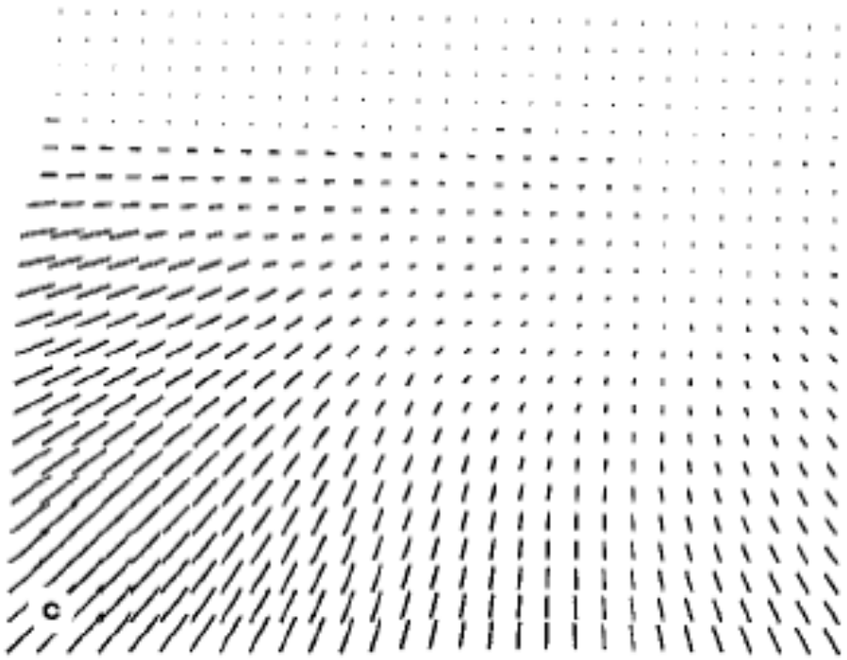


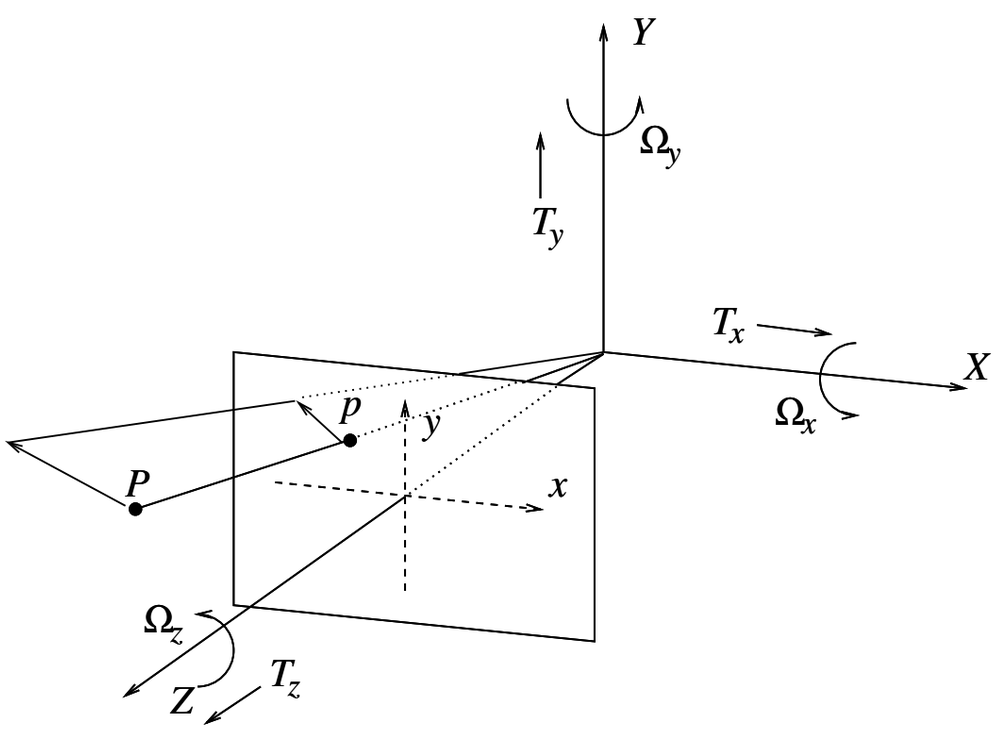
J. J. Gibson, The Ecological Approach to Visual Perception

Optical Flow Field

Image irradiance at time t and location $\mathbf{x} = (x, y)$:

$$I(x, y, t)$$



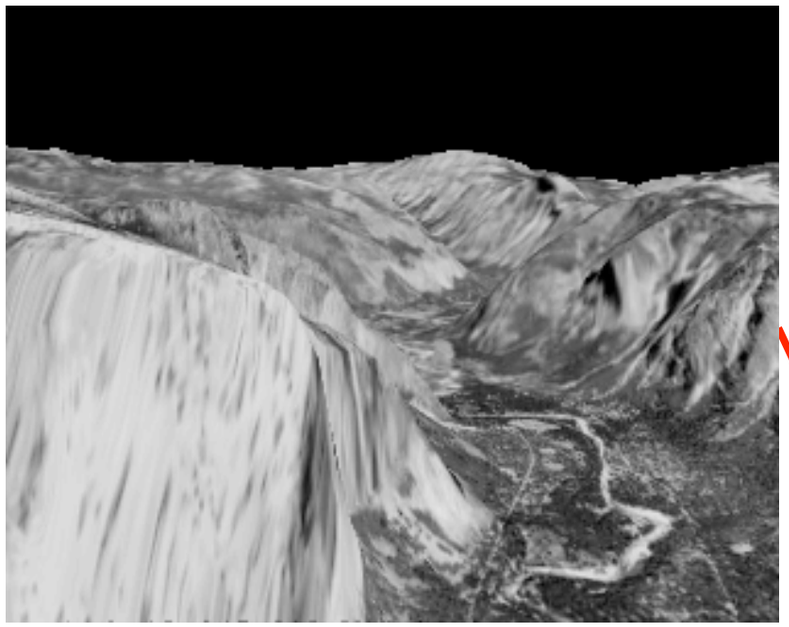


$u(x, y)$ Horizontal component

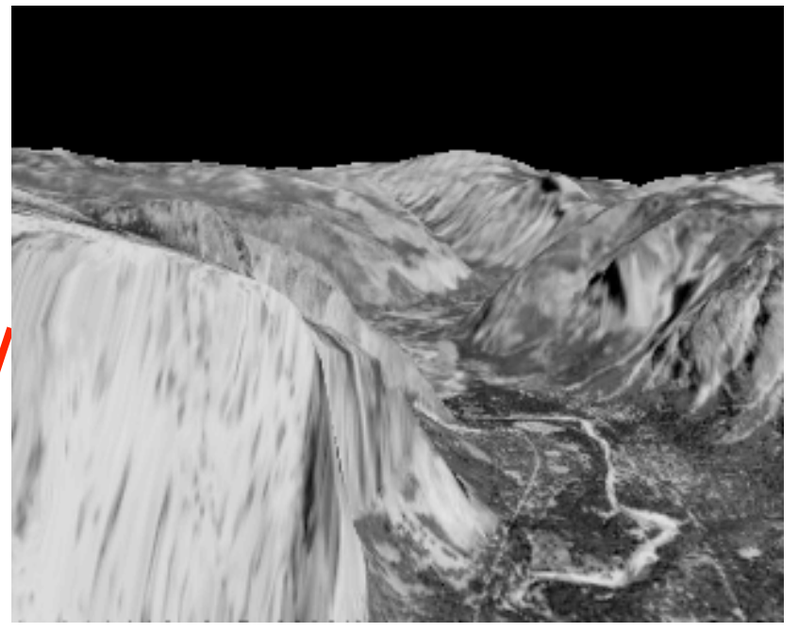
$v(x, y)$ Vertical component

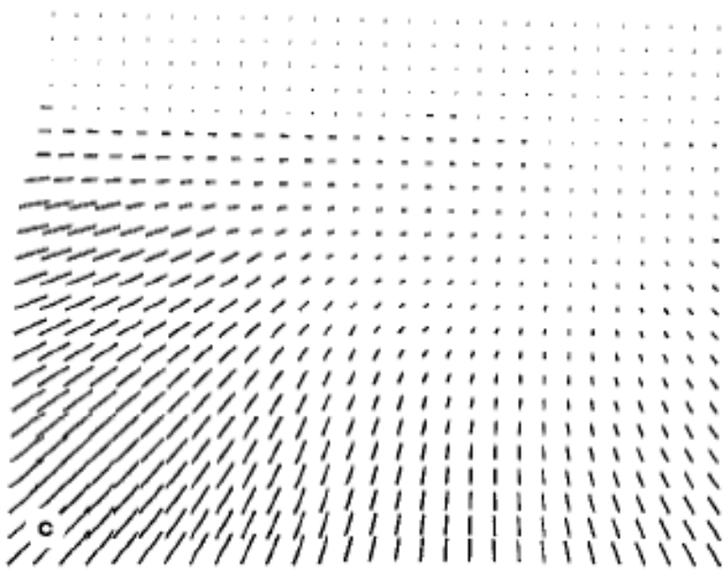
Optical Flow Estimation

time t

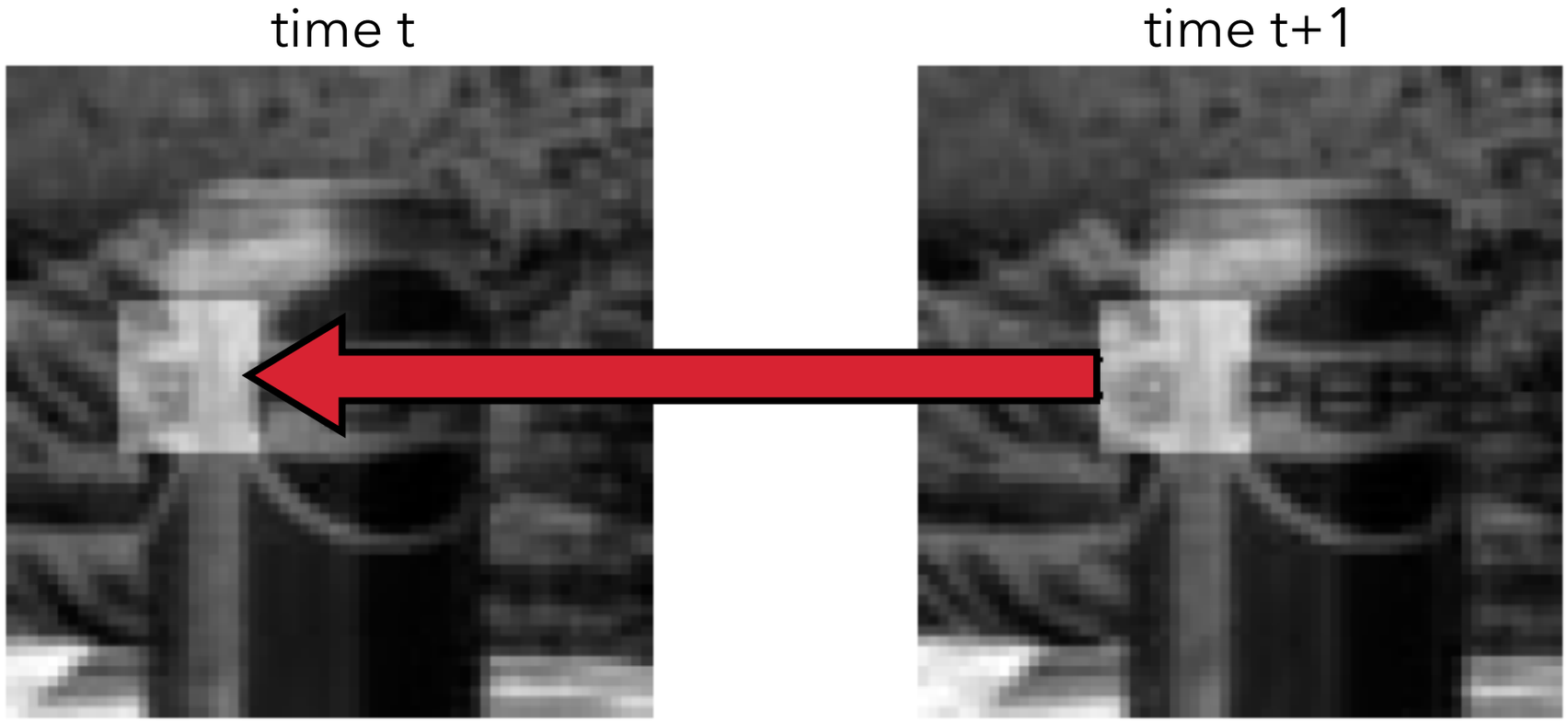


time t+1





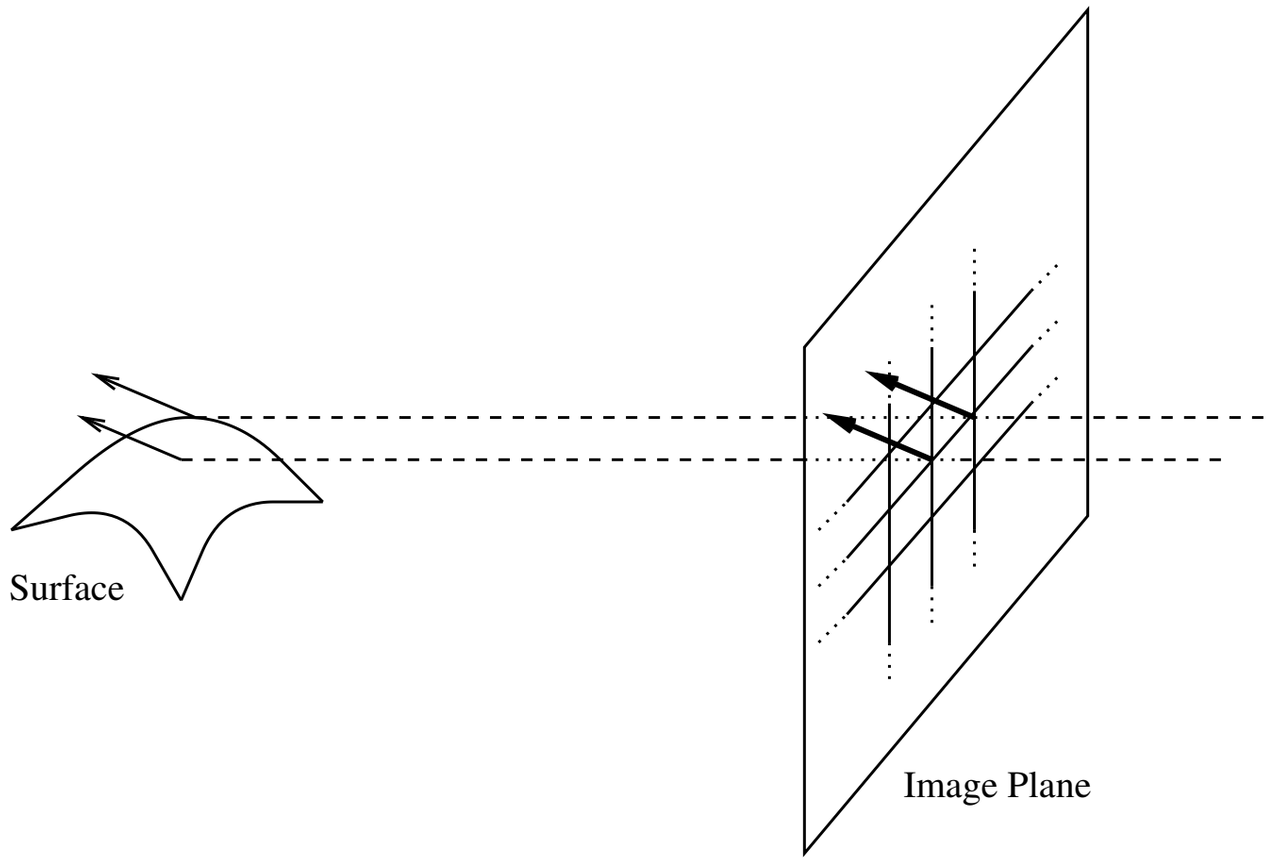
Brightness Constancy



Assumption 1:

Image measurements (e.g. brightness) in a small region remain the same although their location may change.

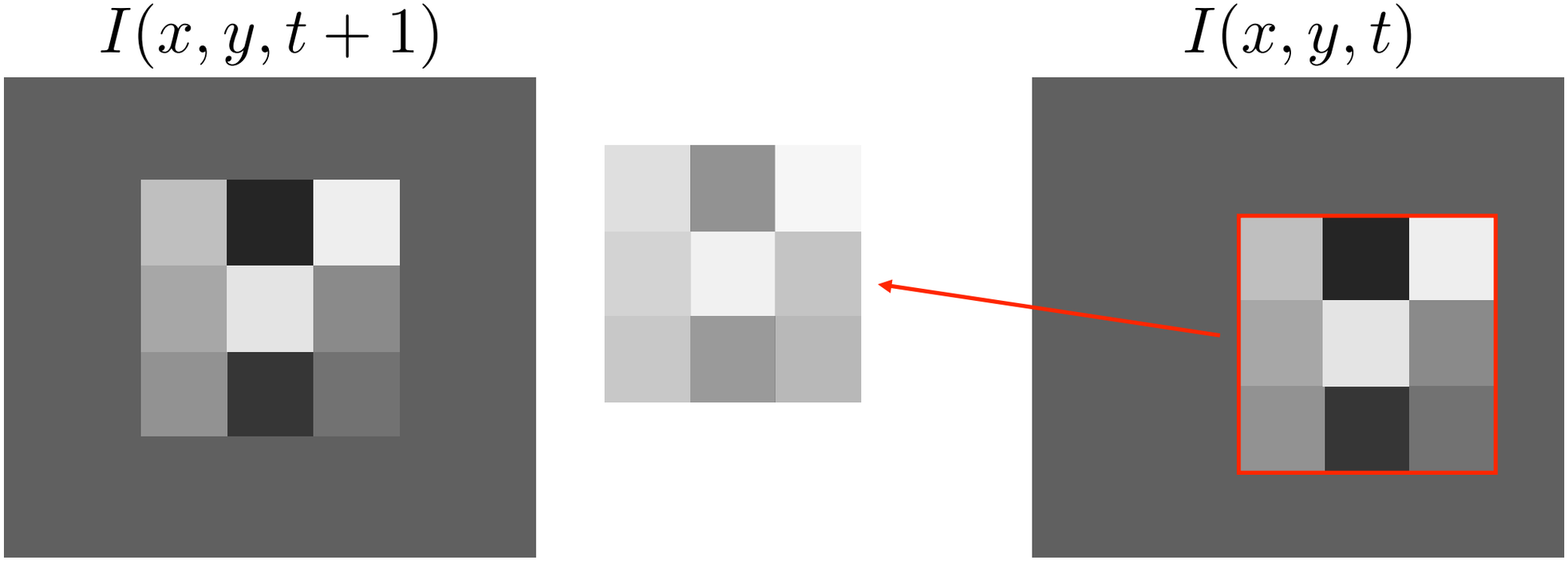
Spatial Coherence



Assumption 2:

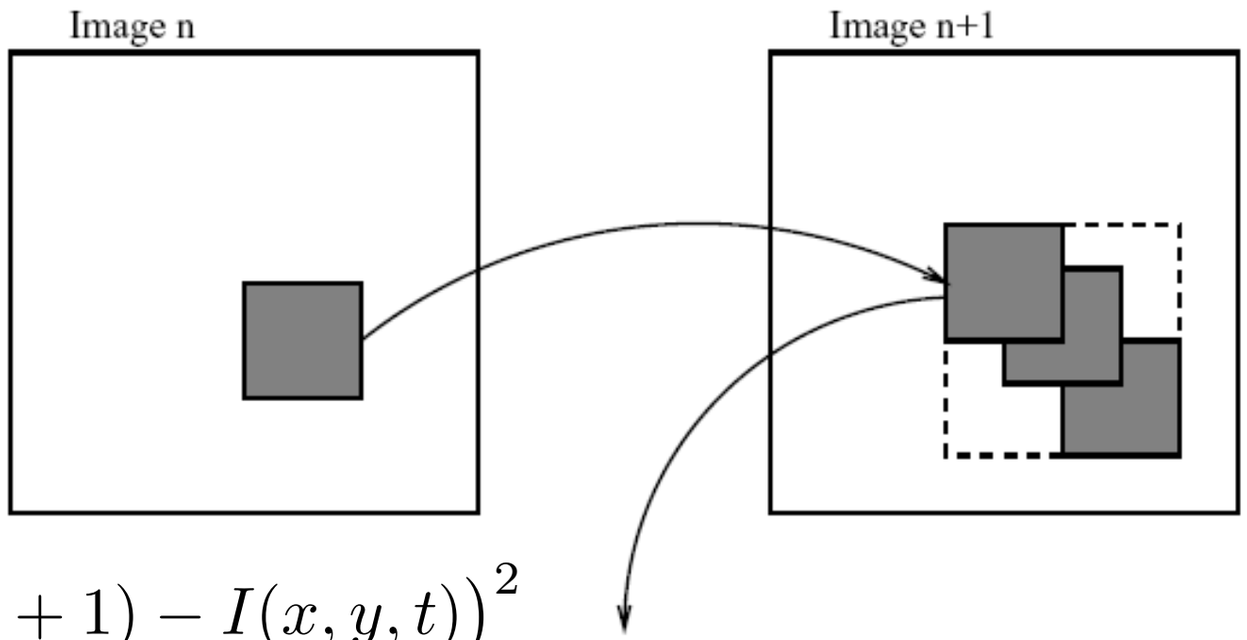
- Neighboring points in the scene typically belong to the same surface and hence typically have similar 3D motions.
- Since they also project to nearby points in the image, we expect spatial coherence in the image flow.

Minimize Brightness Difference

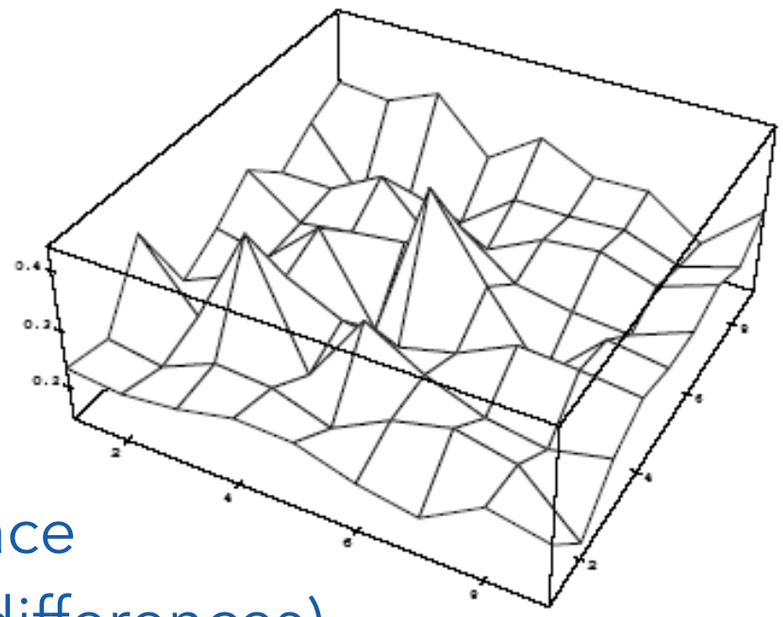


$$E_{SSD}(u, v) = \sum_{(x,y) \in R} \left(I(x + u, y + v, t + 1) - I(x, y, t) \right)^2$$

Sum of Squared Differences



$$E_{SSD}(u,v) = \sum_{(x,y)\in R} \big(I(x+u,y+v,t+1) - I(x,y,t)\big)^2$$



SSD surface
(sum of squared differences)

Aperture Problem

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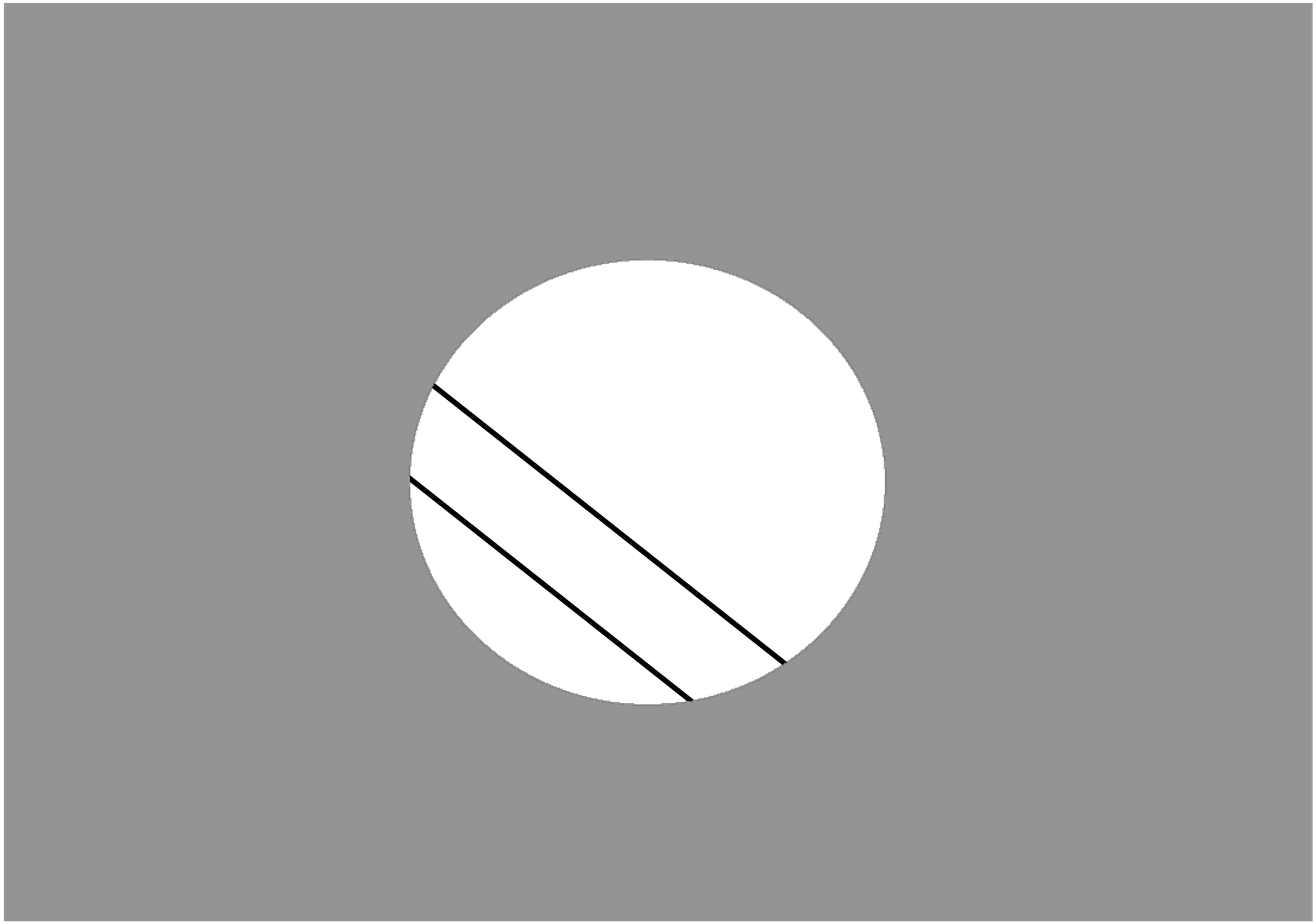

Aperture Problem

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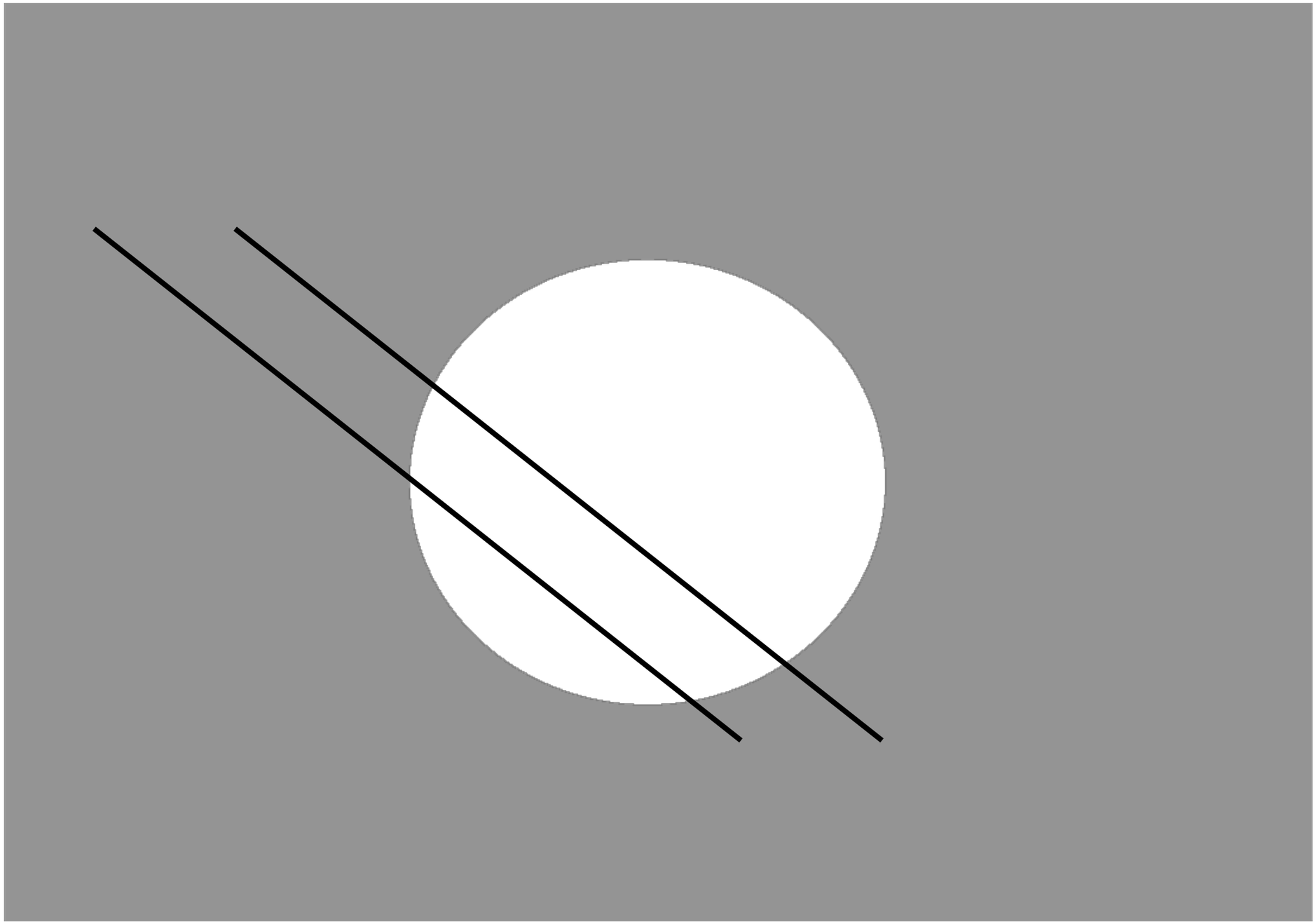

Aperture Problem

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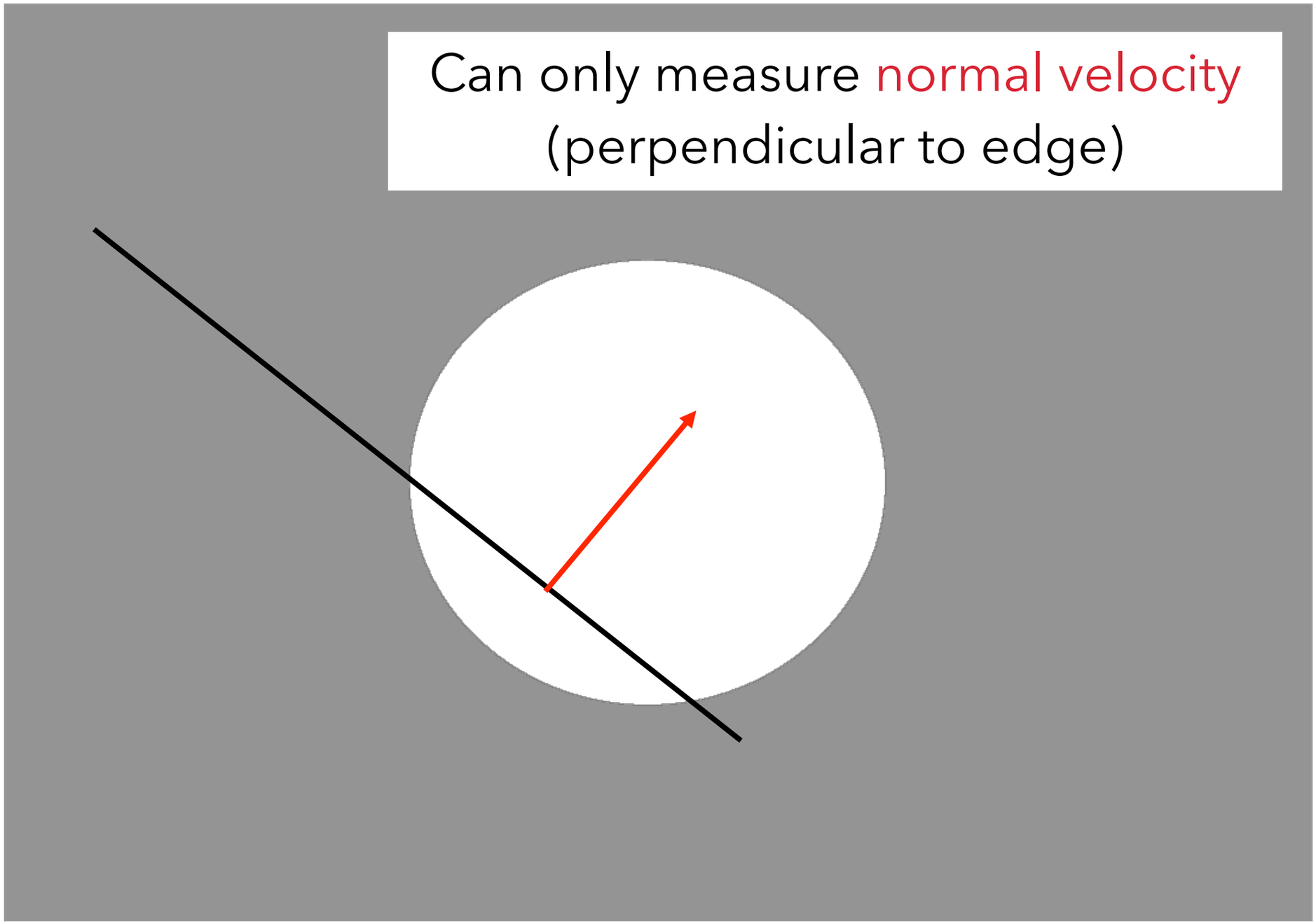
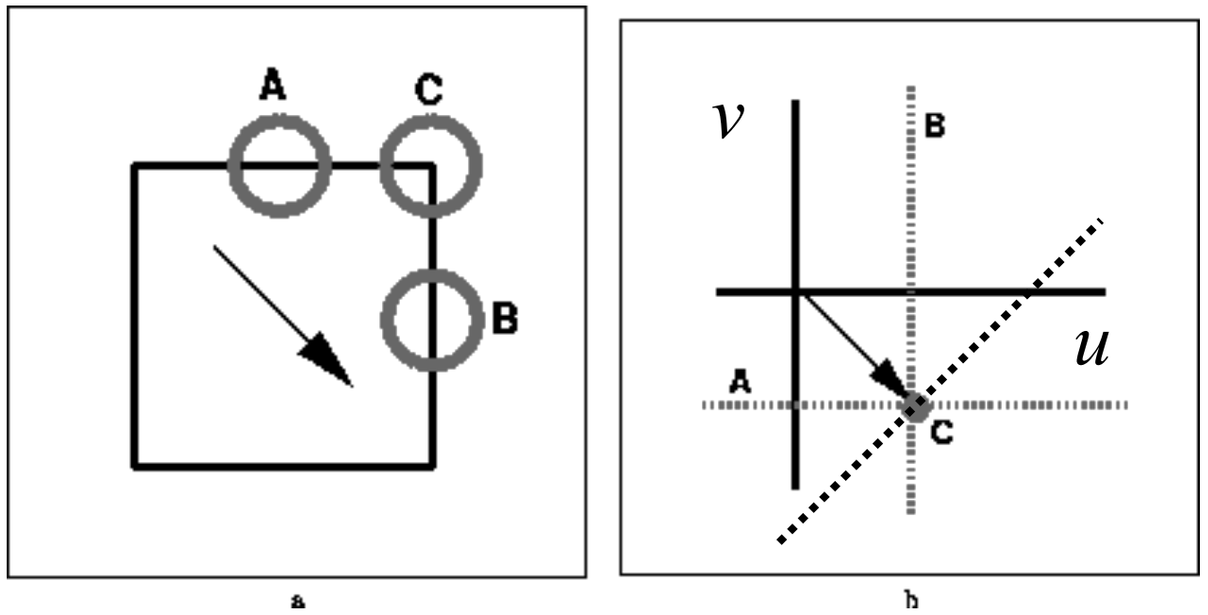


Multiple Constraints



[Yair Weiss]

Combine multiple constraints to get an estimate of the velocity (not only the normal component).

Area-Based Flow

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- How do we combine multiple constraints?
  - Remember our assumptions.
  - We will assume spatial smoothness of the flow.
- More specifically:
  - Assume that the flow is constant in a region.

$$E_{SSD}(u,v) \approx \sum_{(x,y)\in R} \left(u \cdot I_x(x,y,t) + v \cdot I_y(x,y,t) + I_t(x,y,t)\right)^2$$

  - This is what we have been doing (sliding window).
- But how do we solve for the motion?

Solving for u

$$\mathbf{u} = -\left(\sum_R \nabla I \nabla I^{\mathrm{T}}\right)^{-1} \left(\sum_R I_t \nabla I\right)$$

- This is a classical flow technique:

  B. D. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. IJCAI, pp. 674–679, 1981.

- Use this to compute dense optical flow
  - Iterative estimation.
  - Coarse-to-fine estimation.

Do we get good results?

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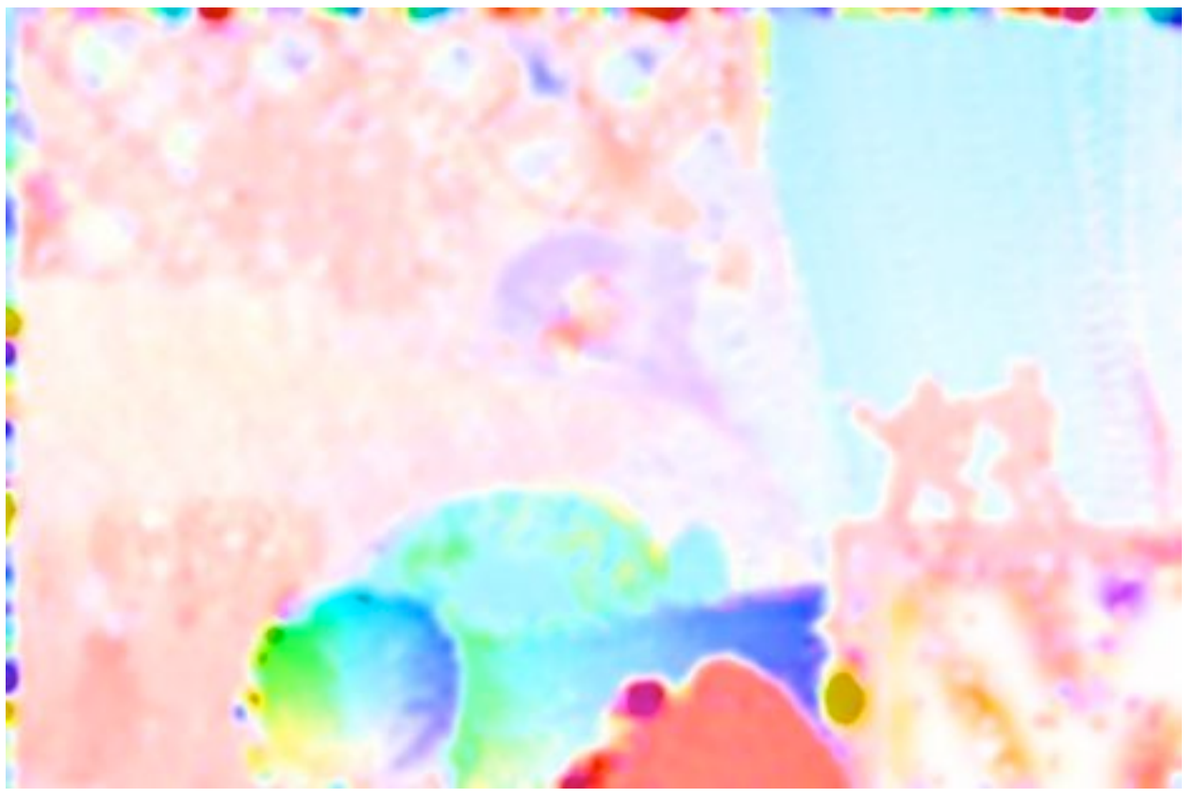
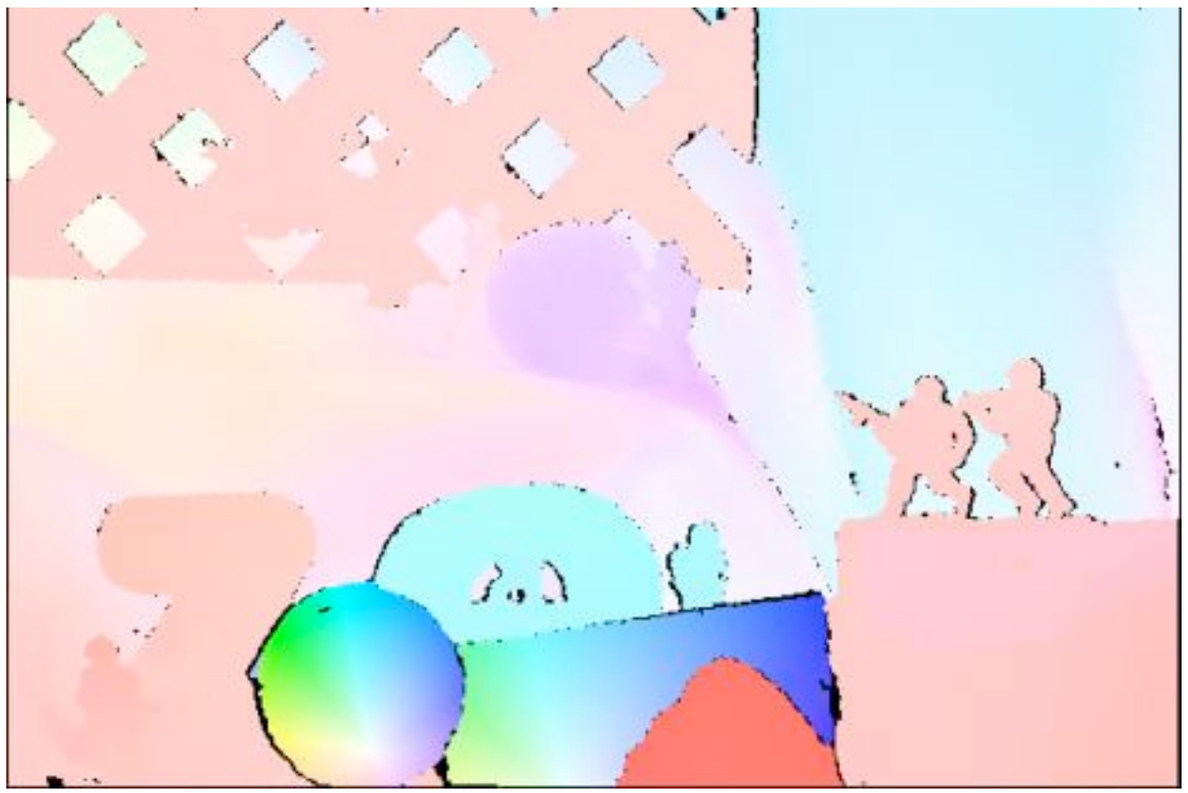
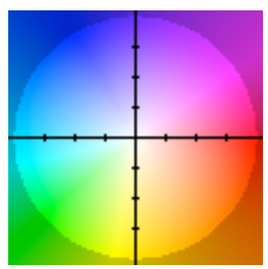
- Not really...



Pyramid LK method



Ground truth



What is the problem?

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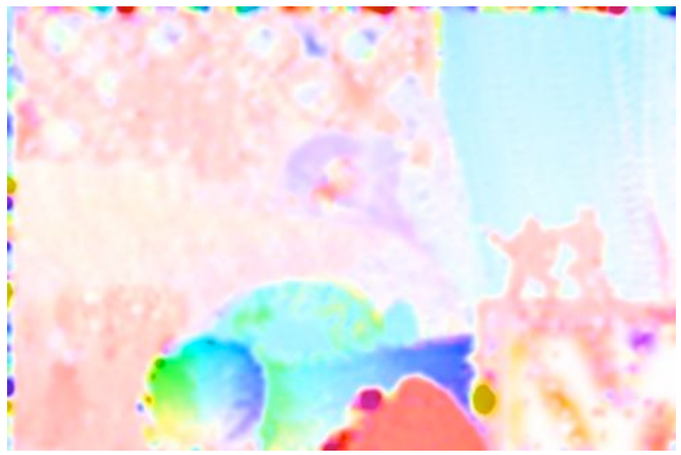
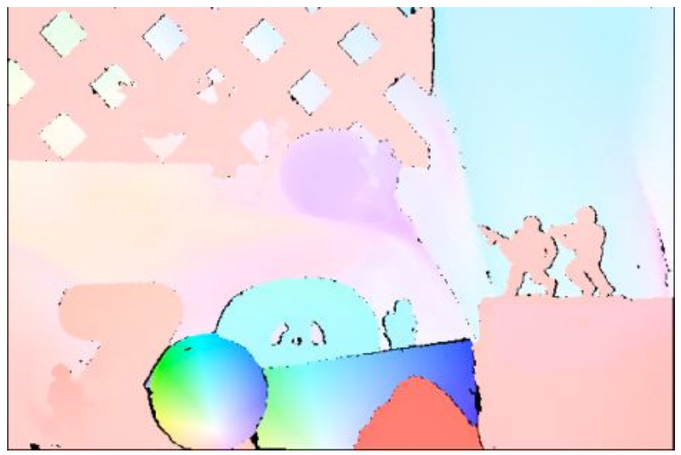
- The window is **too big**!
  - All the discontinuities in the flow are smoothed over.
  - But discontinuities do exist, e.g., at motion boundaries.



- But: The window is also **too small**!
  - In some areas, the flow is really bad, because there is not enough image information in the window.
  - This happens in areas with little texture.



- LK is a local optical flow method.
  - Global flow methods to the rescue