UNIVERSITY OF SOUTH CAROLINA

CSCE 574 ROBOTICS

Computer Vision

Slides courtesy of Professor Gregory Dudek and Alberto Quattrini Li

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Why vision?

- Passive (emits nothing).
  - Discreet.
  - Energy efficient.
- Intuitive.
- Powerful (works well for us, right?)
- Long and short range.
- Fast.

So, what's the problem?

- How hard is vision? Why do we think is do-able?

Problems:

- Slow.
- Data-heavy.
- Impossible.
- Mixes up many factors.

Data heavy

From GoPro HERO3+ at Barbados 2015 Field Trials

$$\begin{array}{ccc} & 1920 & \\ 1080 & \begin{bmatrix} 43 & 43 & 42 & 40 & 39 & \cdots & 29 & 29 & 31 & 33 \\ 42 & 41 & 40 & 39 & 38 & \cdots & 31 & 32 & 35 & 37 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ldots & \vdots & \vdots & \vdots & \vdots \\ 54 & 57 & 60 & 62 & 66 & \cdots & 42 & 43 & 56 & 46 \end{bmatrix} & \text{R} \end{array}$$

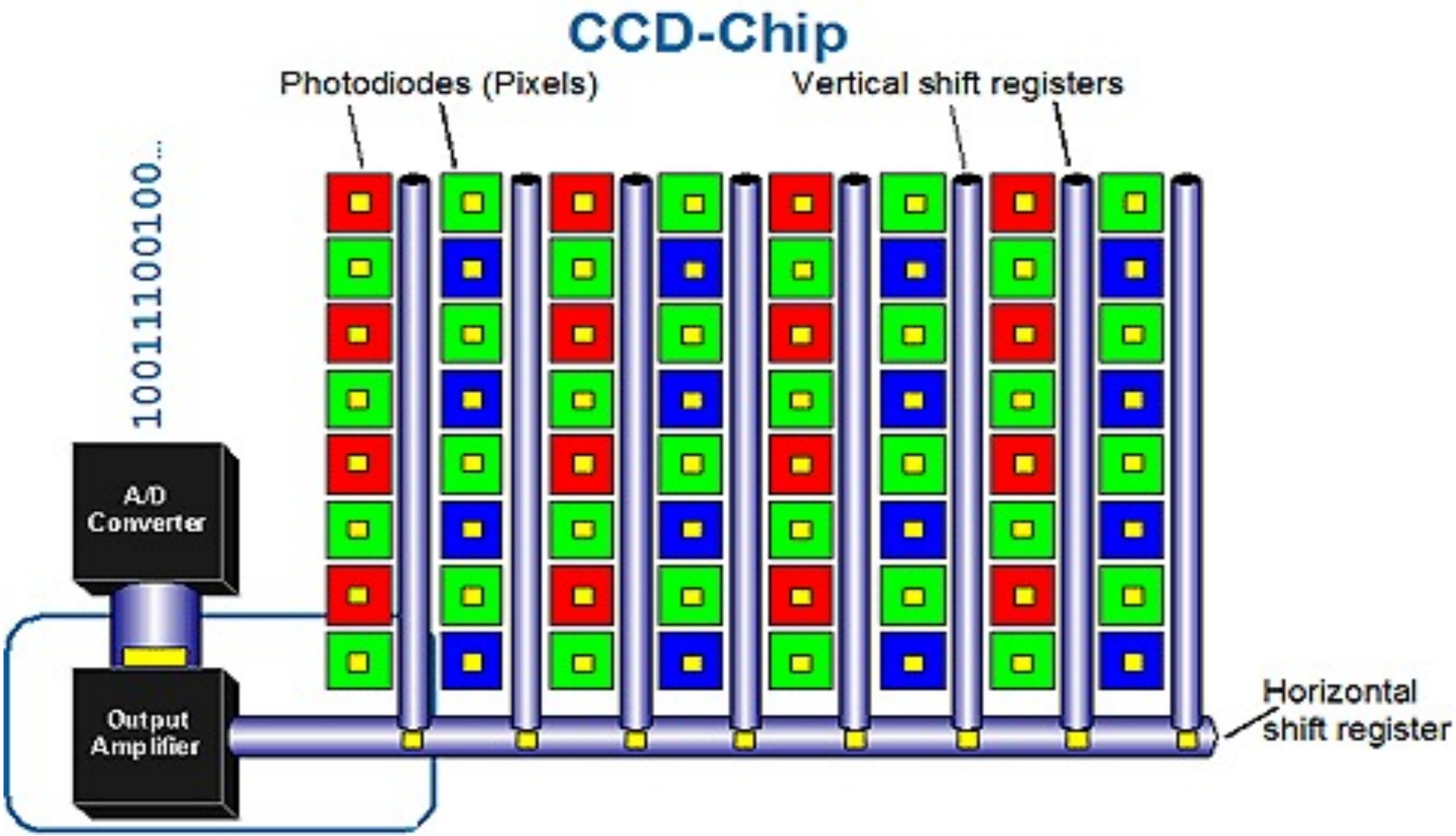
$$\begin{array}{cc} 1080 & \begin{bmatrix} 129 & 129 & 129 & 129 & 128 & \cdots & 149 & 149 & 151 & 153 \\ 128 & 128 & 127 & 128 & 127 & \cdots & 151 & 152 & 155 & 157 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ldots & \vdots & \vdots & \vdots & \vdots \\ 146 & 146 & 148 & 148 & 148 & \cdots & 149 & 150 & 151 & 152 \end{bmatrix} & \text{G} \end{array}$$

$$\begin{array}{cc} 1080 & \begin{bmatrix} 146 & 146 & 146 & 145 & 146 & \cdots & 166 & 166 & 168 & 170 \\ 145 & 145 & 144 & 144 & 145 & \cdots & 168 & 169 & 172 & 174 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ldots & \vdots & \vdots & \vdots & \vdots \\ 159 & 160 & 160 & 161 & 162 & \cdots & 165 & 166 & 165 & 166 \end{bmatrix} & \text{B} \end{array}$$

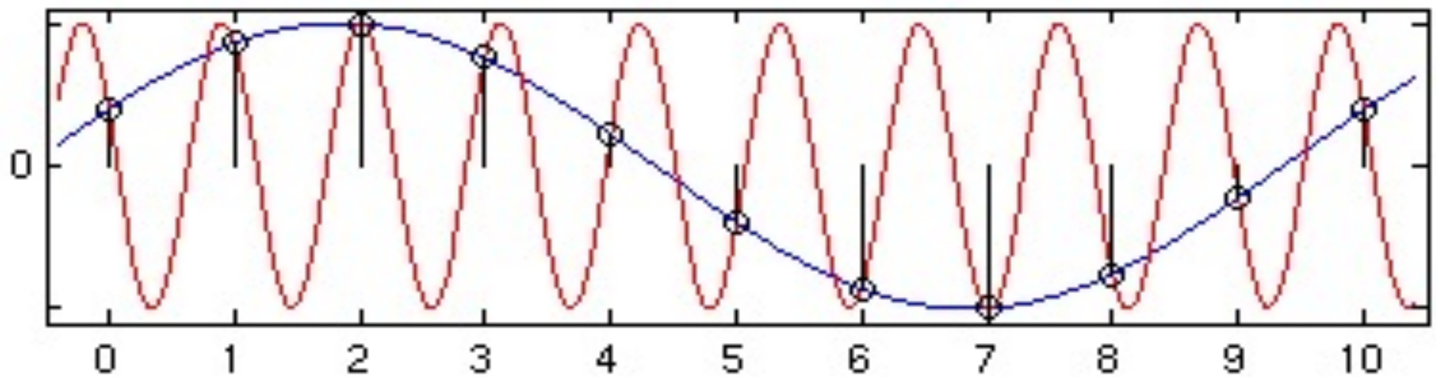
Aliasing

- Images are not actually continuous.
- The sampling (and hardware) issues lead to a few other minor problems.

Aliasing

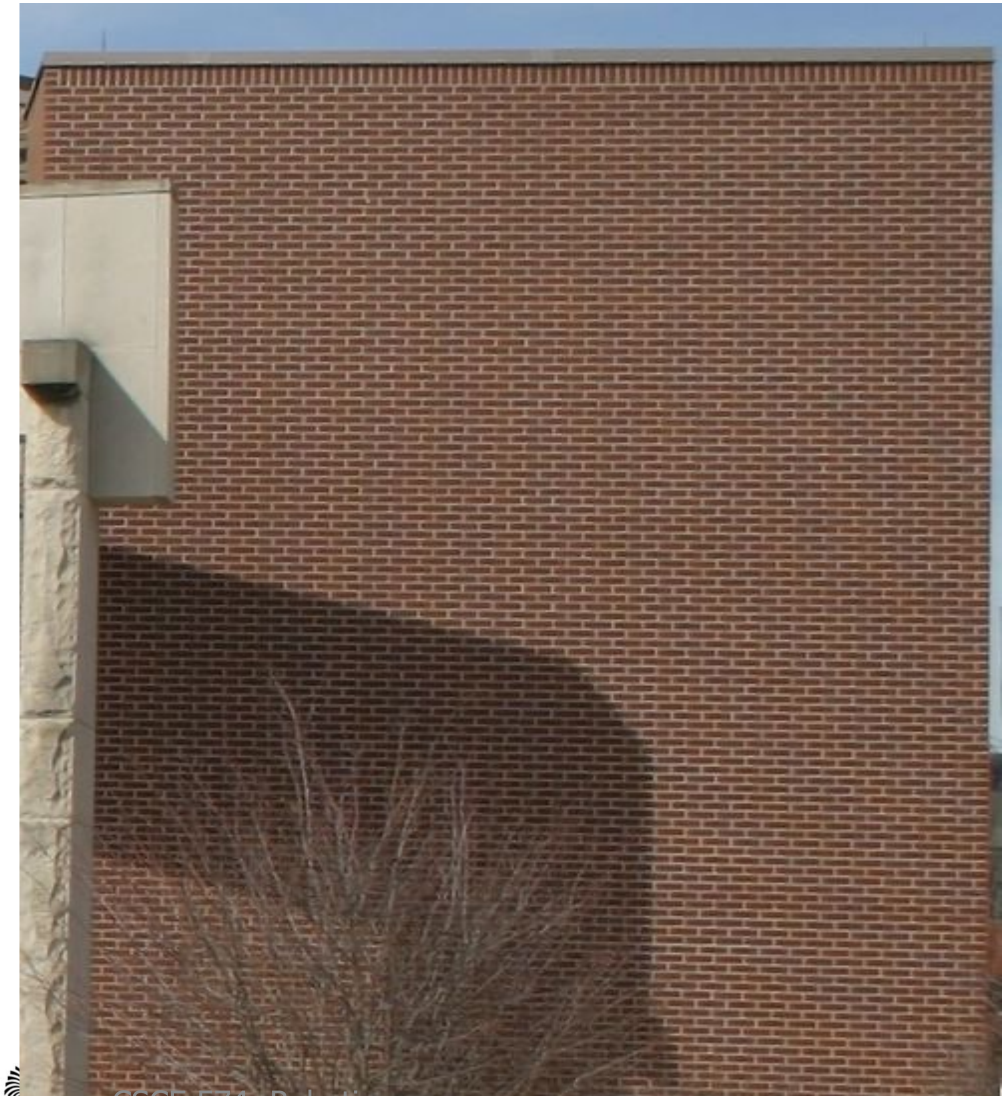

CCD-Chip
Photodiodes (Pixels)
Vertical shift registers
100111100100...
A/D Converter
Output Amplifier
Horizontal shift register

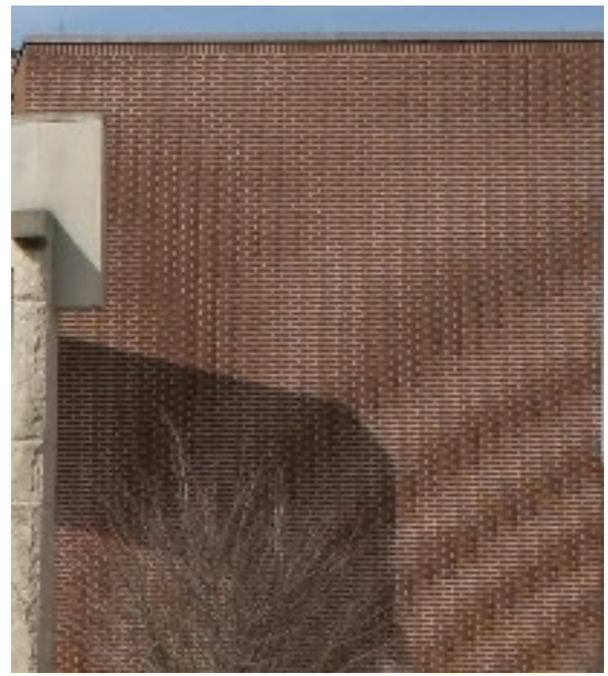
Aliasing



- To avoid: $f_{sampling} > 2F_{max}$
  - Nyquist Rate

Aliasing: Moiré Patterns





Ill-posed

- What a camera does to the 3d world...

Shigeo Fukuda

squeezes away one dimension

http://www.psychologie.tu-dresden.de/i1/kaw/diverses Material/www.illusionworks.com/html/art_of_shigeo_fukuda.html

Ill-posed

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Ill-posed

- In trying to extract 3d structure from 2d images, vision is an *ill-posed* problem.

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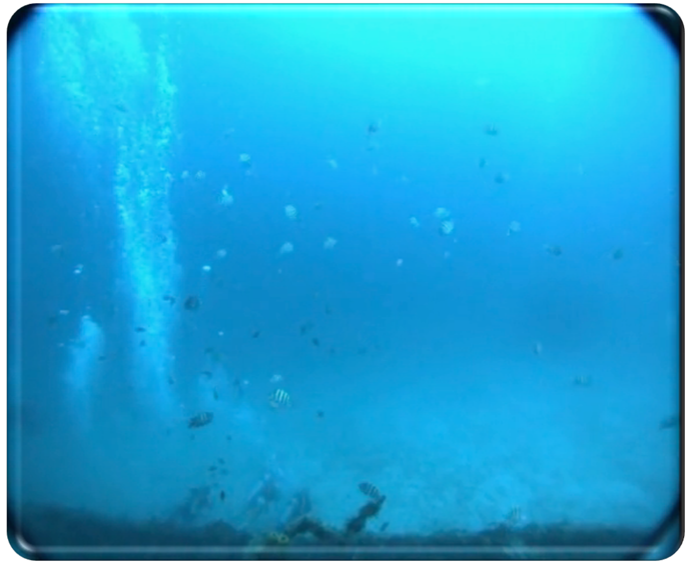
Ill-posed

- In trying to extract 3d structure from 2d images, vision is an *ill-posed* problem.

  – An image isn't enough to disambiguate the many possible 3d worlds that could have produced it.

Difficult scenarios

- In certain settings, such as the underwater, robotic vision is particularly challenging
  - Different lighting conditions
  - Color loss
  - Hazing and blur
  - Texture loss



What does a robot need ?

doesn't need a full interpretation of available images

"This is Prof. X in his office offering me a cup of iced tea."

does need information about what to do...

"Run Away!!"

reactive

- avoiding obstacles (or predators)
- pursuing objects
- localizing itself
- Mapping
- finding targets
- reasoning about the world ...

deliberative

environmental interactions

Key problems

- Recognition:
  - What is that thing in the picture?
  - What are all the things in the image?
- Scene interpretation
  - Describe the image?
- Scene “reconstruction”:
  - What is the 3-dimensional layout of the scene?
  - What are the physical parameters that gave rise to the image?
  - What is a description of the scene?

Notion of an “inverse problem.”

Robot vision sampler

A brief overview of robotic vision processing...

(1) Image streams → simplified via generality
(1) Image streams → simplified via specificity

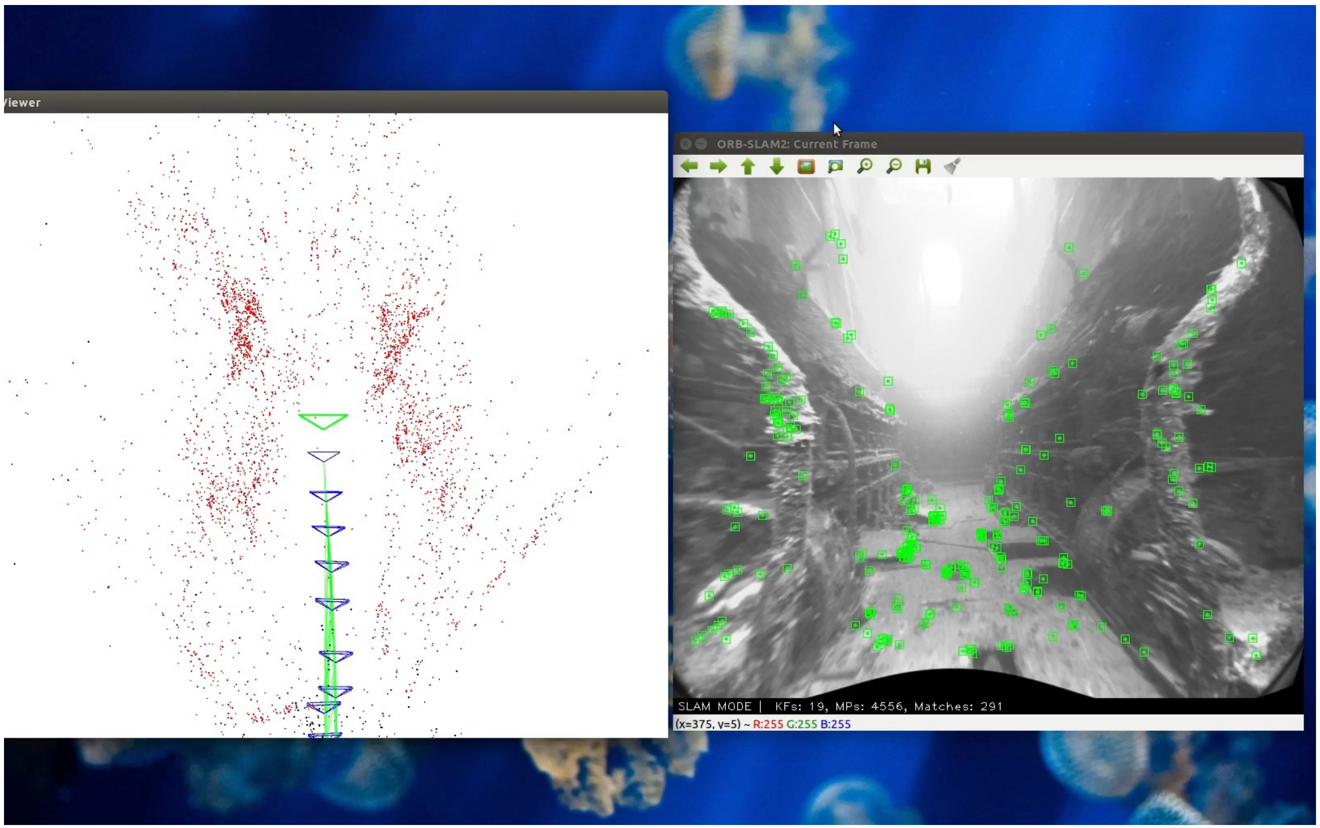
(2) Stereo vision → (or beyond...)

(3) Incorporating vision within robot control

↓ 3d reconstruction

↓ Visual "servoing"

3d reconstruction



Visual Servoing

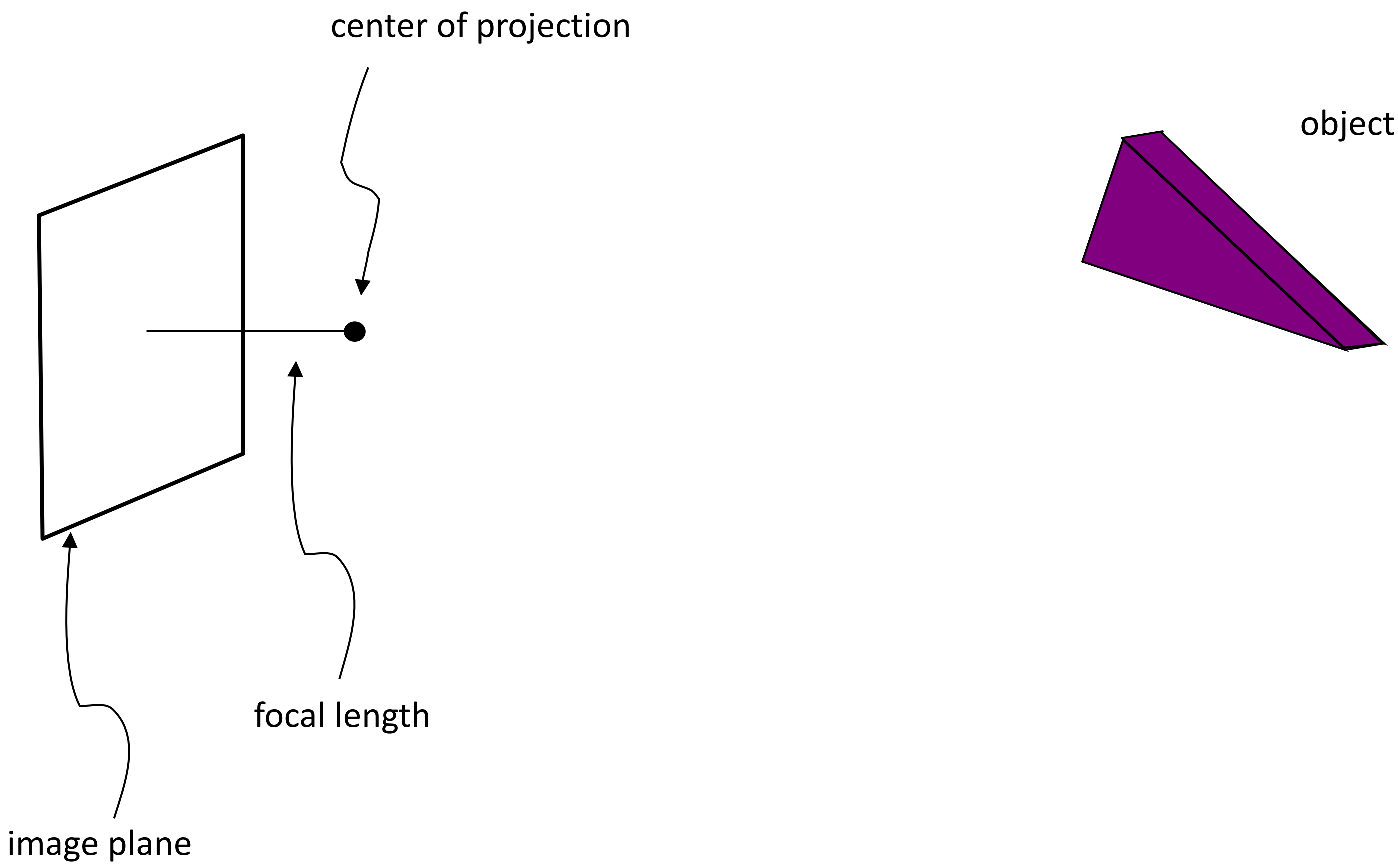
Computer vision algorithms

- Image processing
- Geometric computer vision
- Semantic computer vision

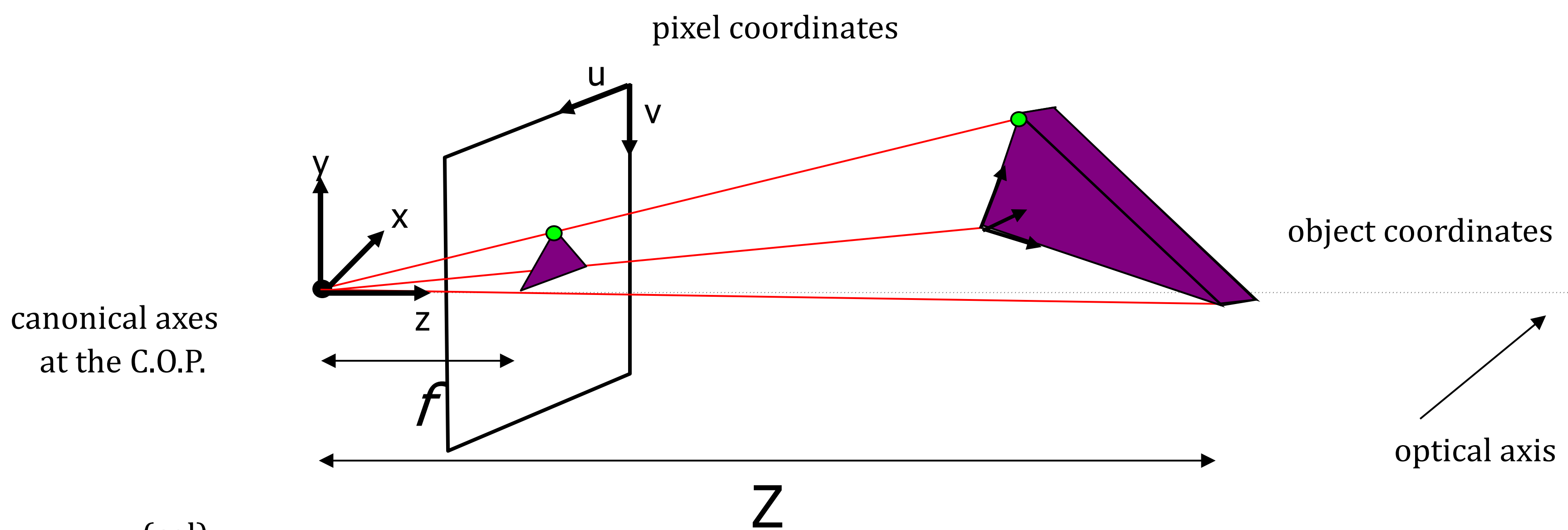
- It is fundamental first to understand image formation

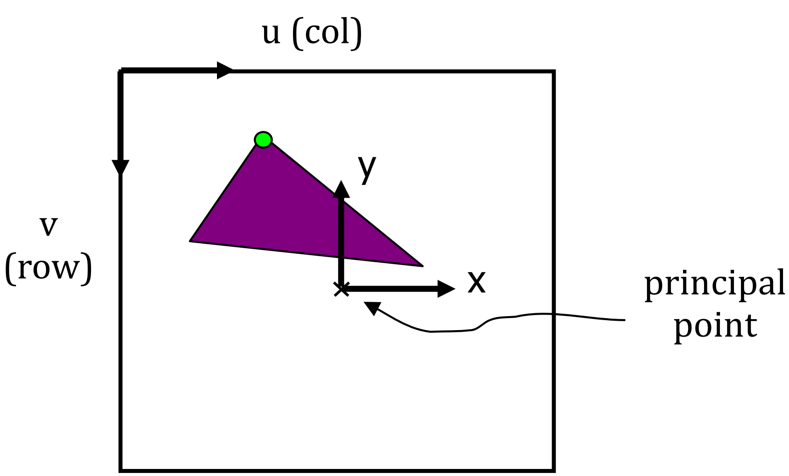
Camera Geometry

3D→2D transformation: perspective projection



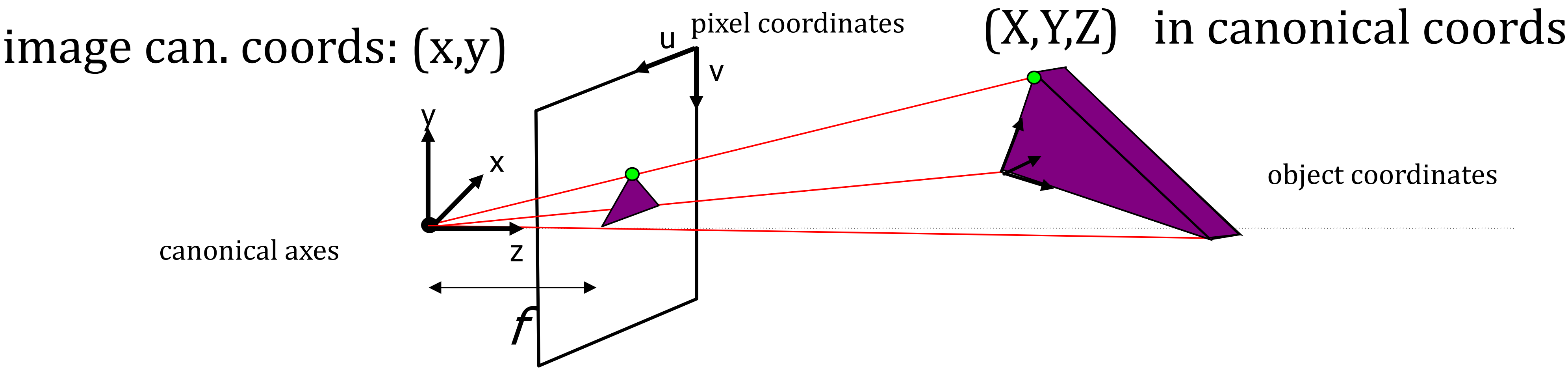
Coordinate Systems



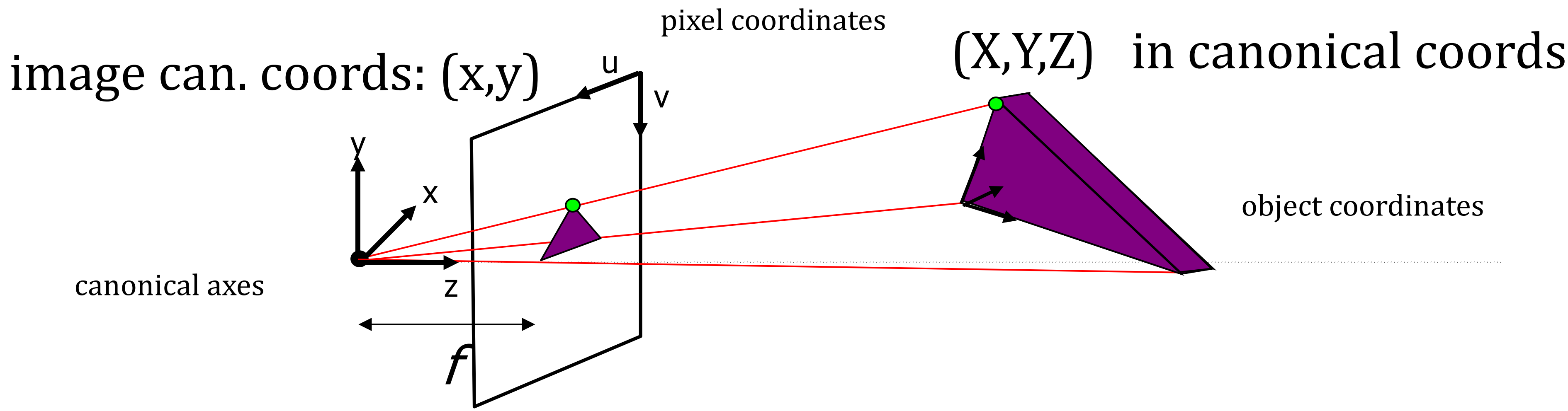


Add coordinate systems in order to describe feature points...

Coordinate Systems



From 3d to 2d



$$x = \frac{fX}{Z} \qquad y = \frac{fY}{Z}$$

a <u>nonlinear</u> transformation

goal: to recover information about (X,Y,Z) from (x,y)

Camera Calibration

- Camera Model
  - [*u v 1*] Pixel coords
  - $[x_w \quad y_w \quad z_w \quad 1]^T$ World coords

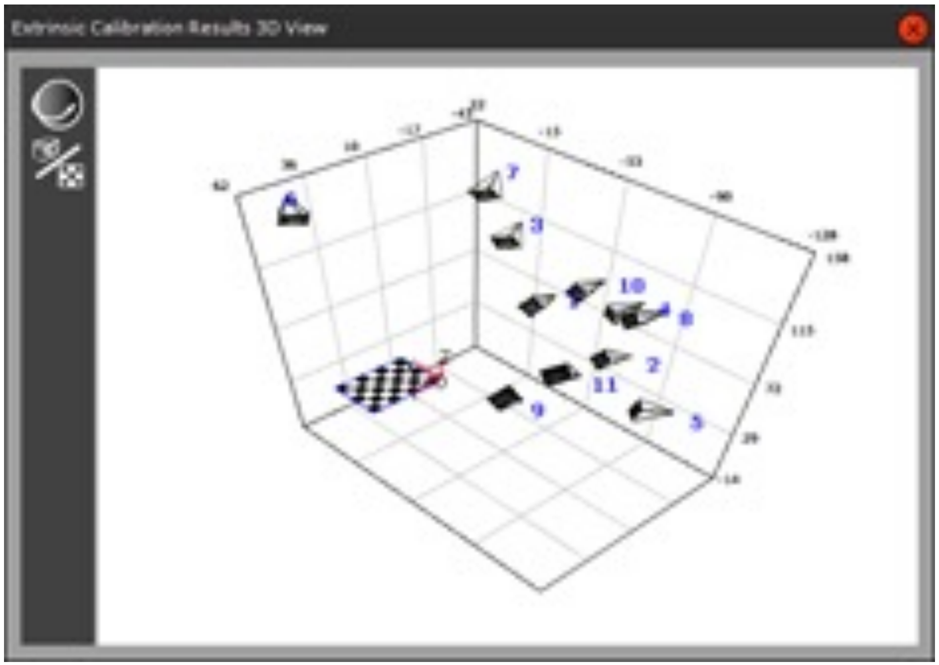
$$z_c \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = A[R \quad T] \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

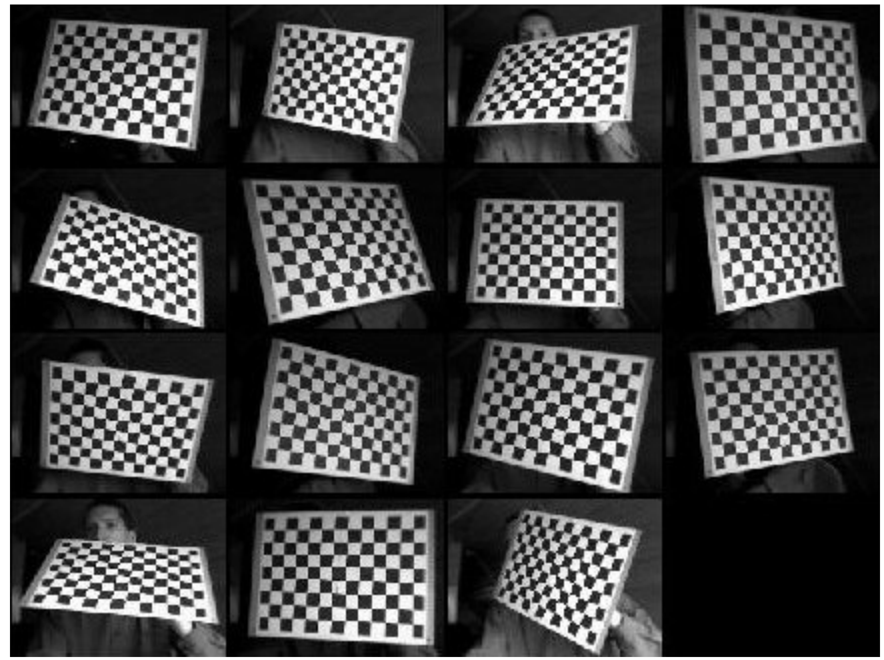
- Intrinsic Parameters
  - $\alpha_x = f \cdot m_x, \alpha_y = f \cdot m_y$ focal lengths in pixels
  - γ skew coefficient
  - u_0, v_o focal point

$$A = \begin{bmatrix} \alpha_x & \gamma & u_0 \\ 0 & \alpha_y & v_o \\ 0 & 0 & 1 \end{bmatrix}$$

- Extrinsic Parameters
  - $[R \quad T]$ Rotation and Translation

Camera Calibration





Existing packages in MATLAB, OpenCV, etc

Rectified Image Sample

Unrectified

Rectified

From Clearpath Husky Axis M1013 camera

Rectified Image Sample

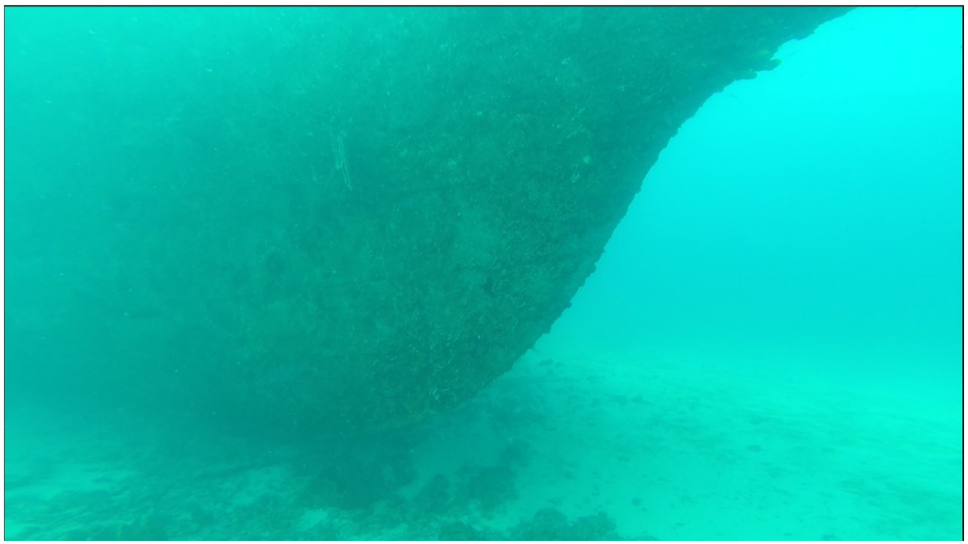
Unrectified

Rectified

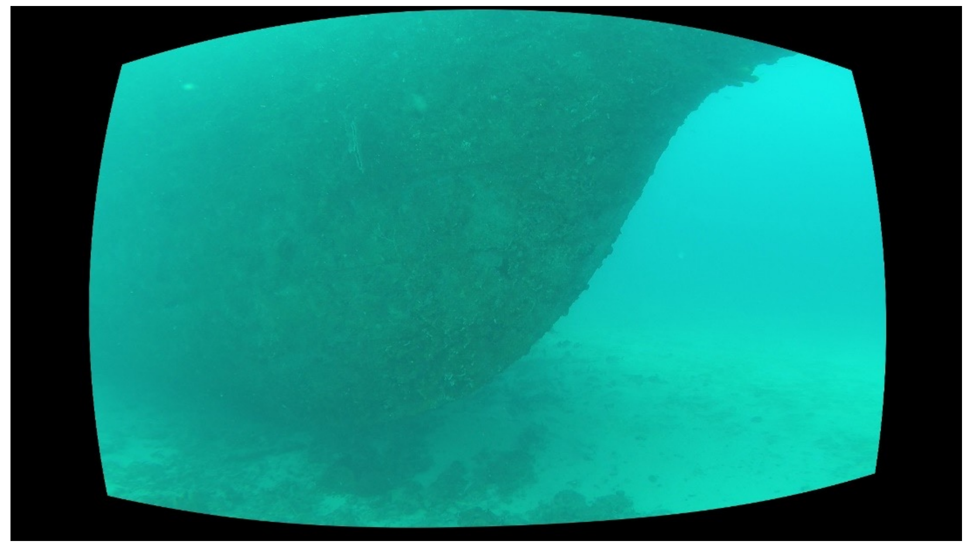
From Parrot ARDrone 2.0 front camera

Rectified Image Sample

Unrectified



Rectified



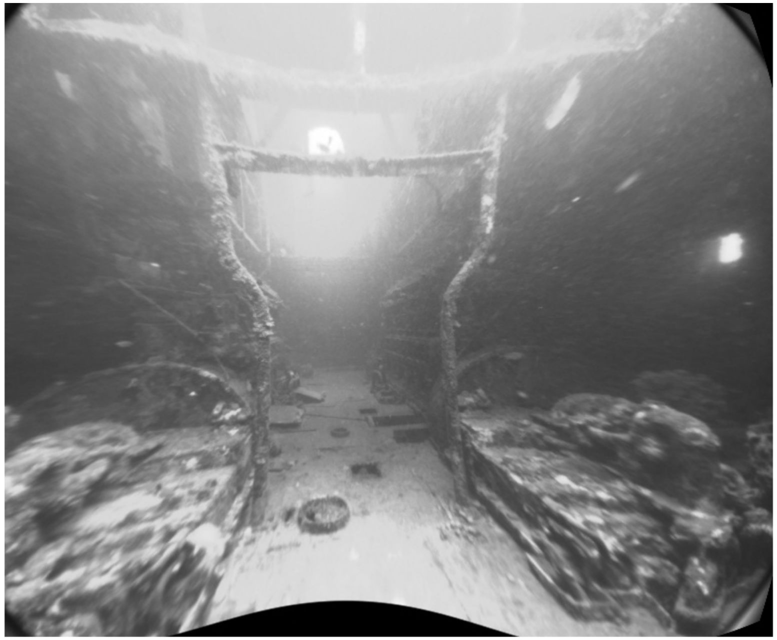
From GoPro HERO3+ at Barbados 2015 Field Trials

ReRectified Image Sample

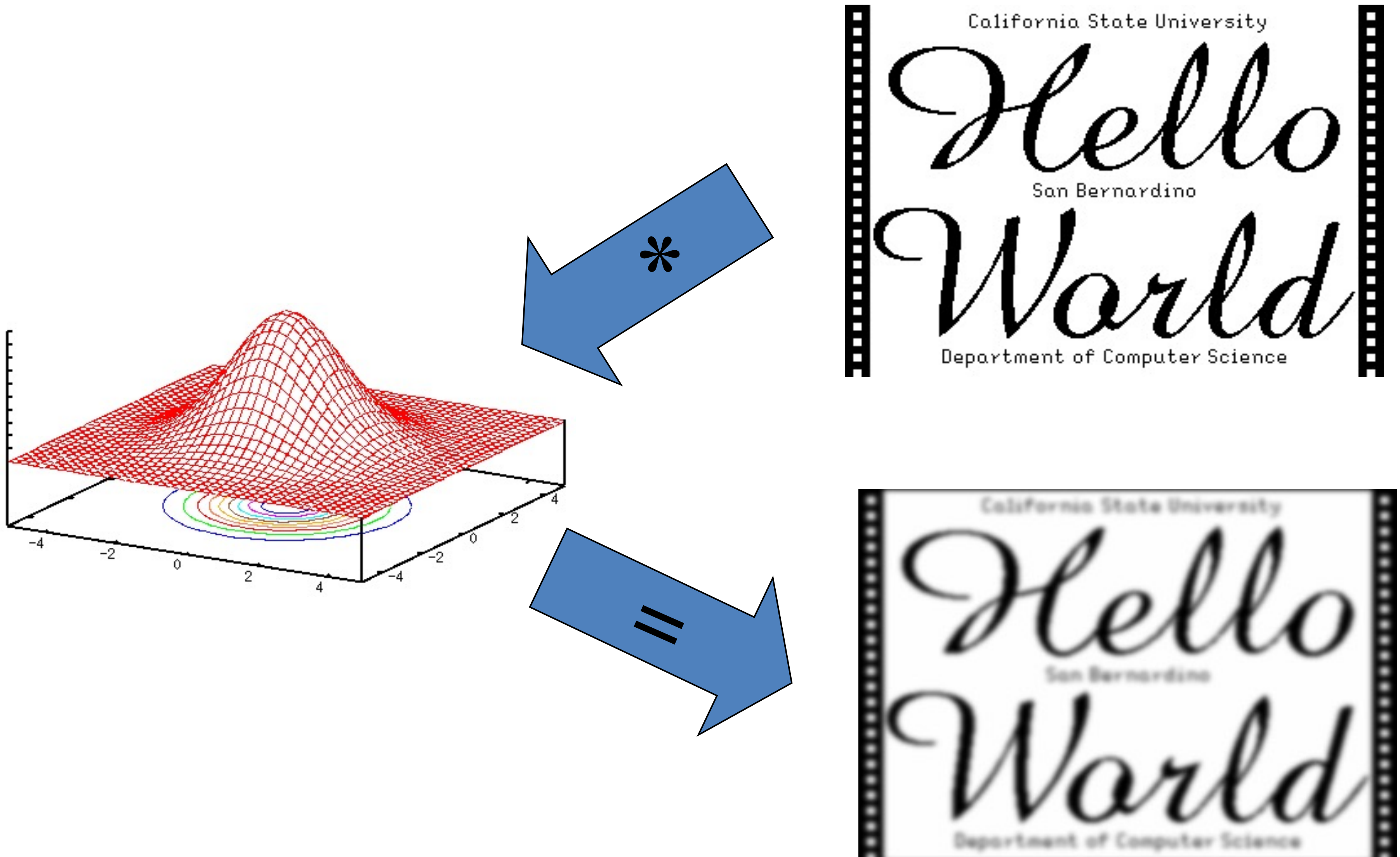
Rectified

From Aqua front camera at Barbados 2013 Field Trials

ReRectified



Gaussian Blur



Gaussian Blur and Noise

$\sigma = 4.0$ pix

$\sigma = 8.0$ pix

$\sigma = 12.0$ pix

$\sigma = 4.0$ pix

$\sigma = 8.0$ pix

$\sigma = 12.0$ pix

Gaussian Blur, Noise, Sobel

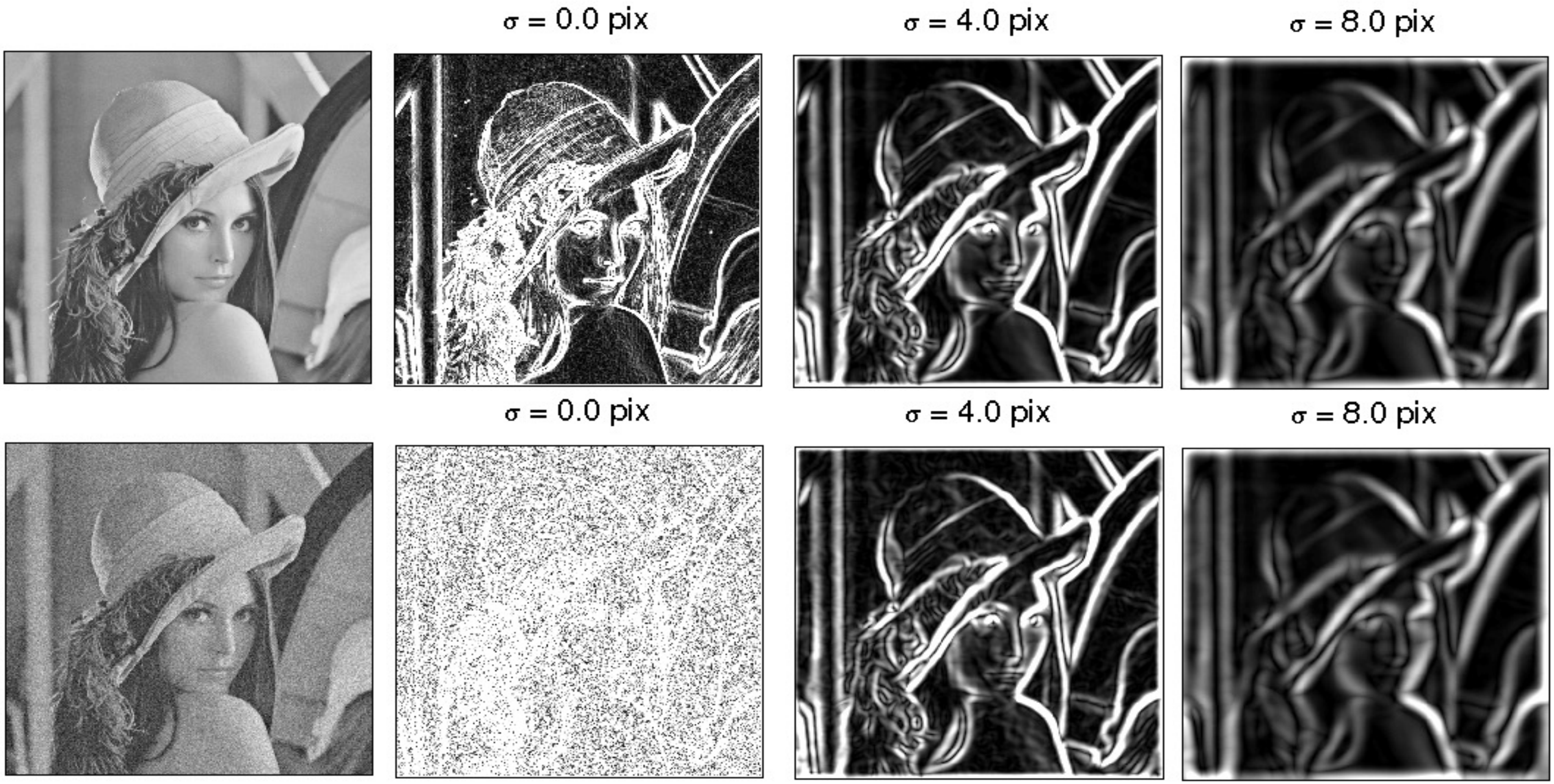
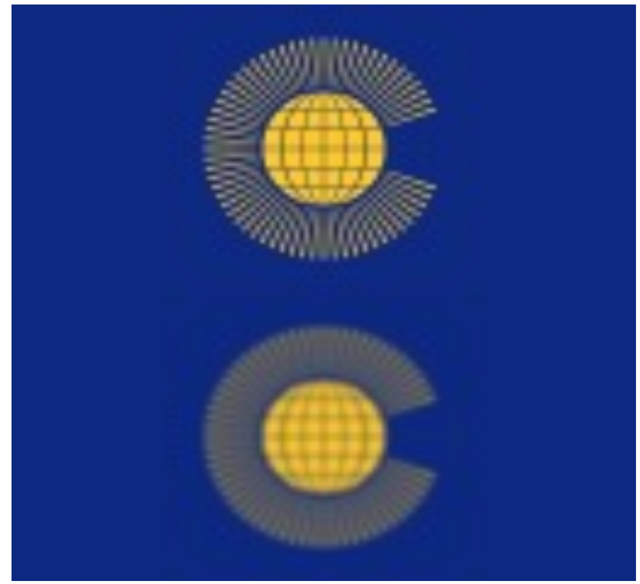
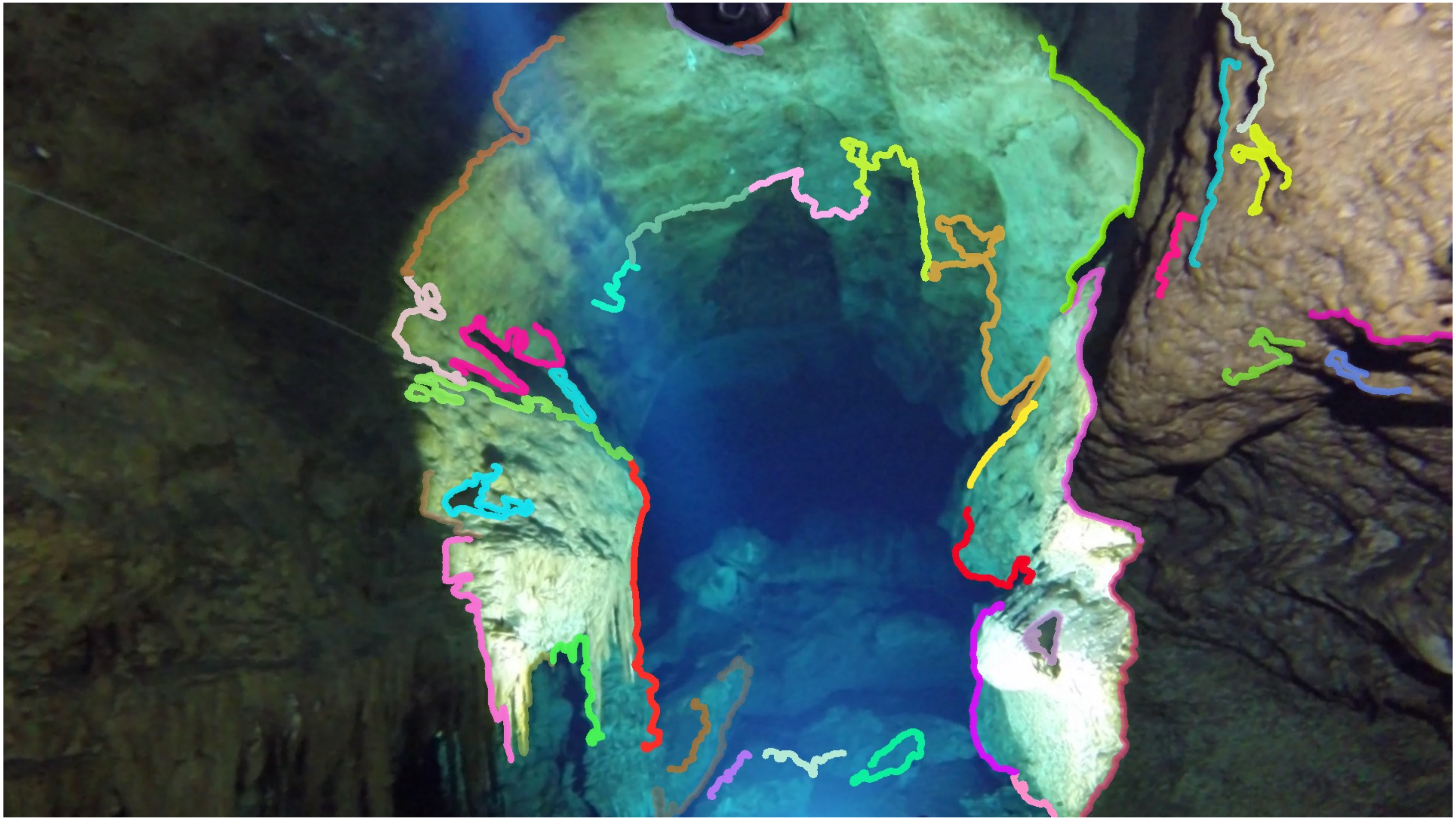


Image Downsampling

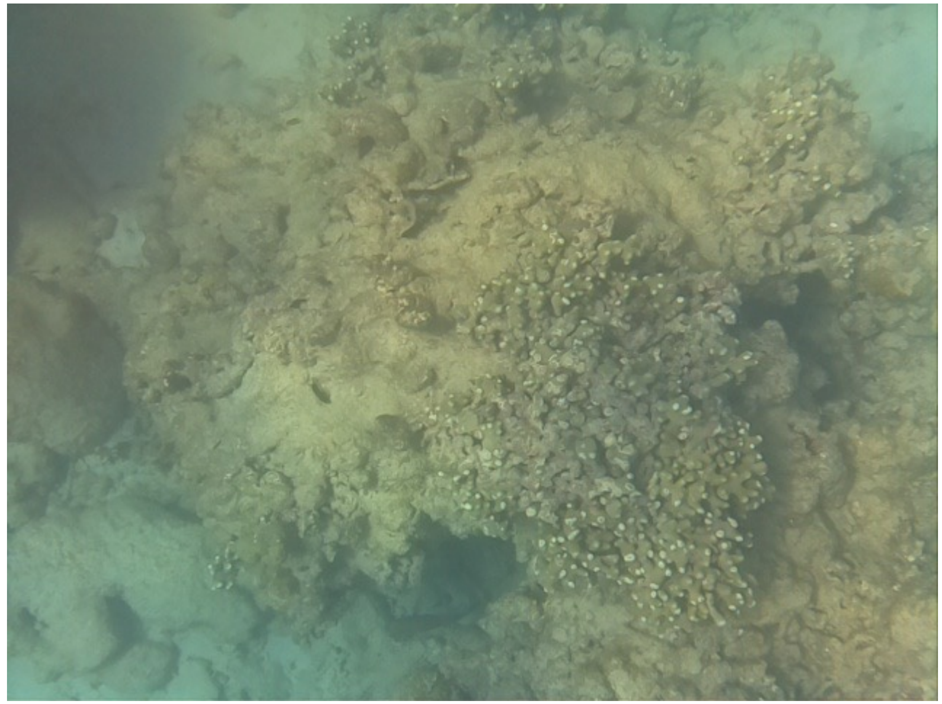


Thresholded image

Edge detection



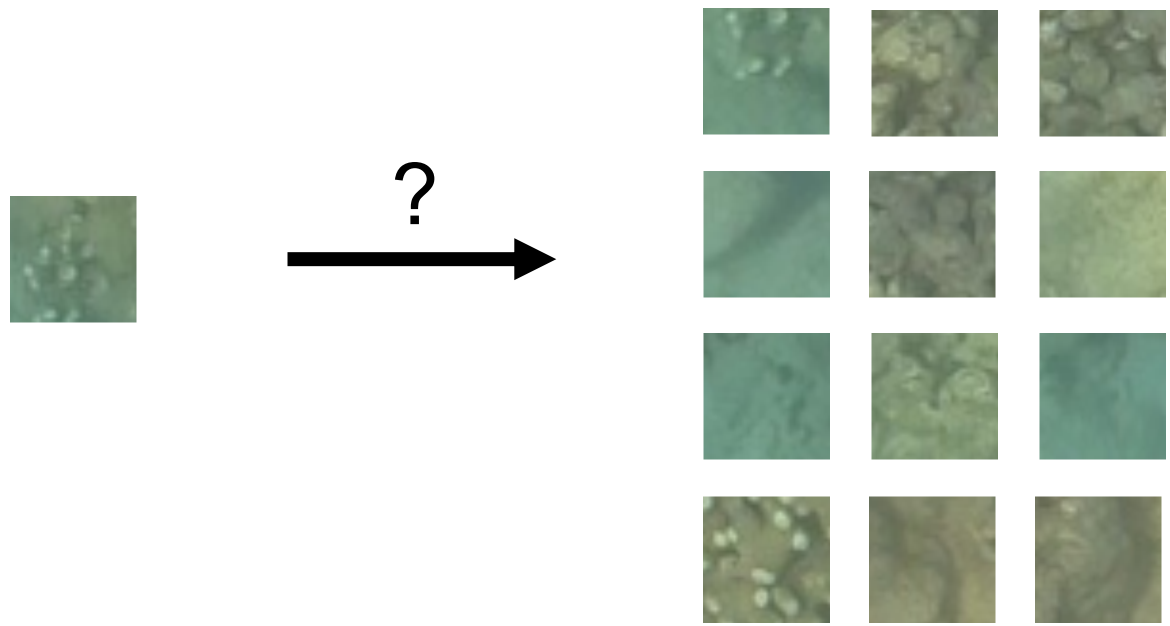
Correspondence Problem



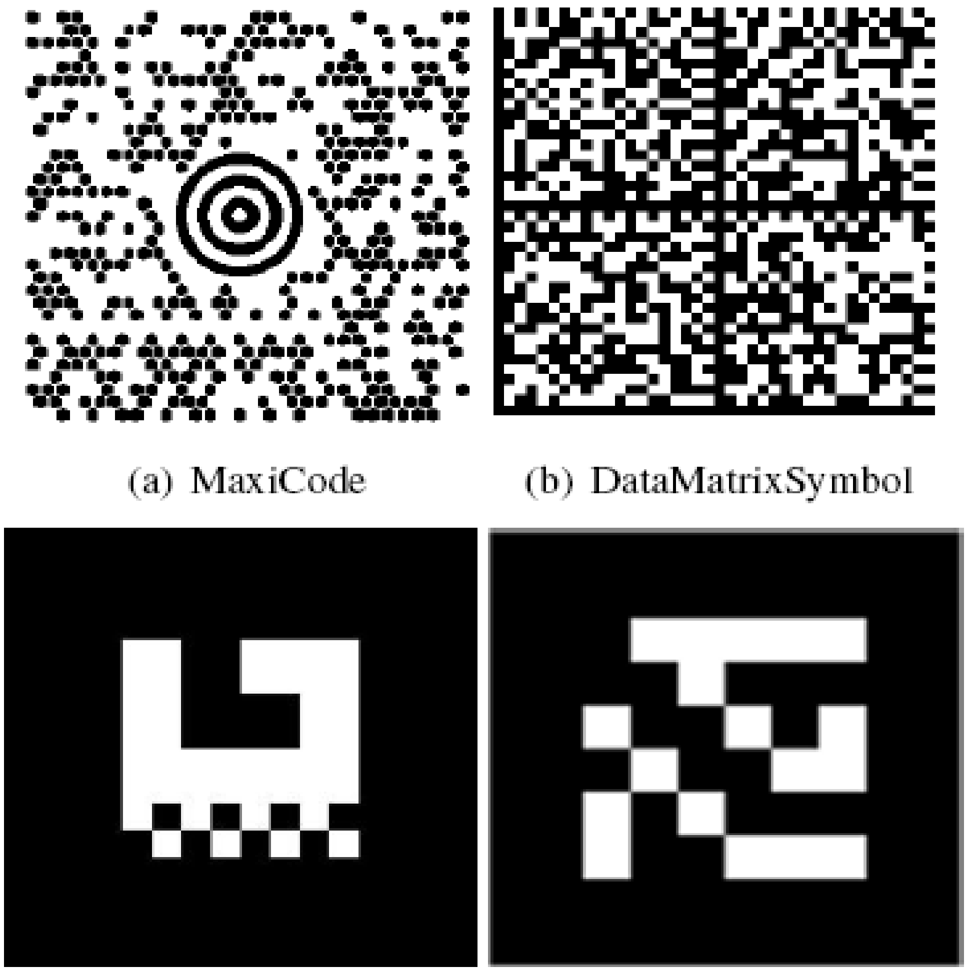
From Raspberry PI camera at Barbados 2016 Field Trials

Correspondence

From I_1 From I_2



Fiduciary Markers/Fiducial



(a) MaxiCode (b) DataMatrixSymbol

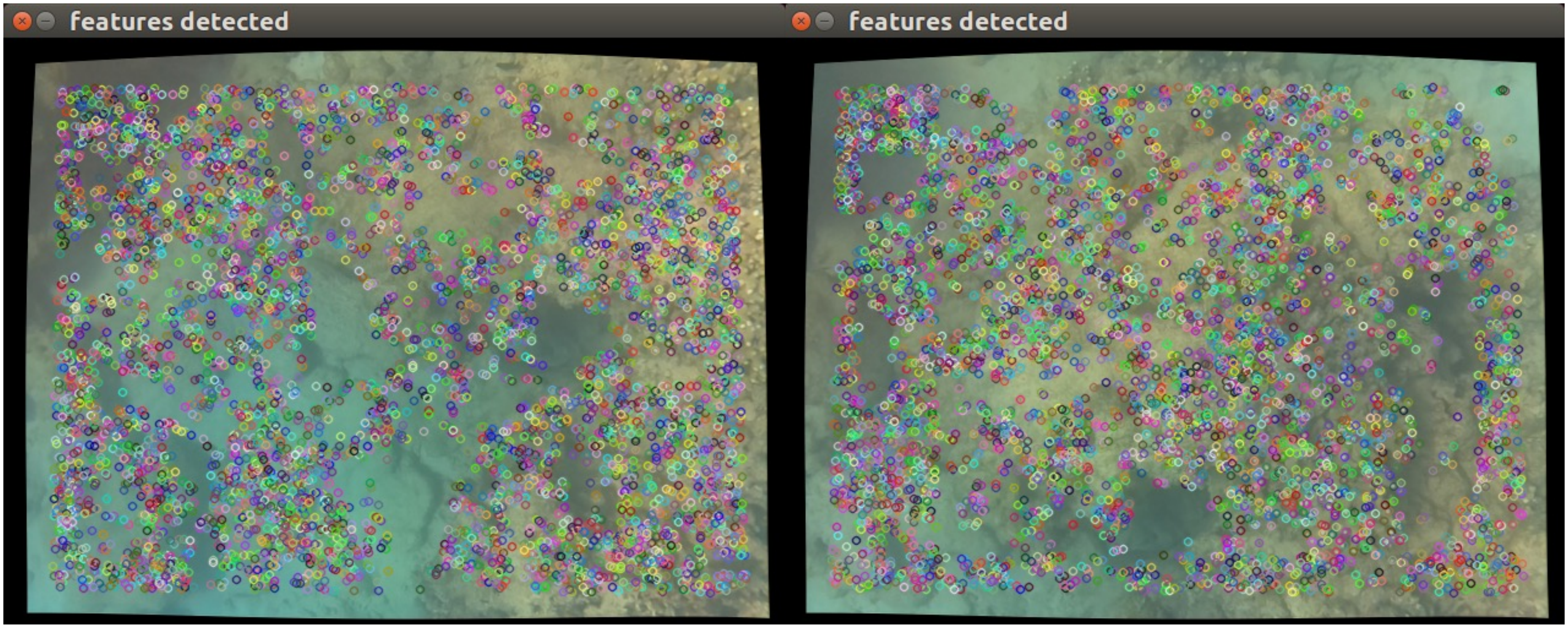
(c) ARToolkit (d) ARTag

Fourier Tag

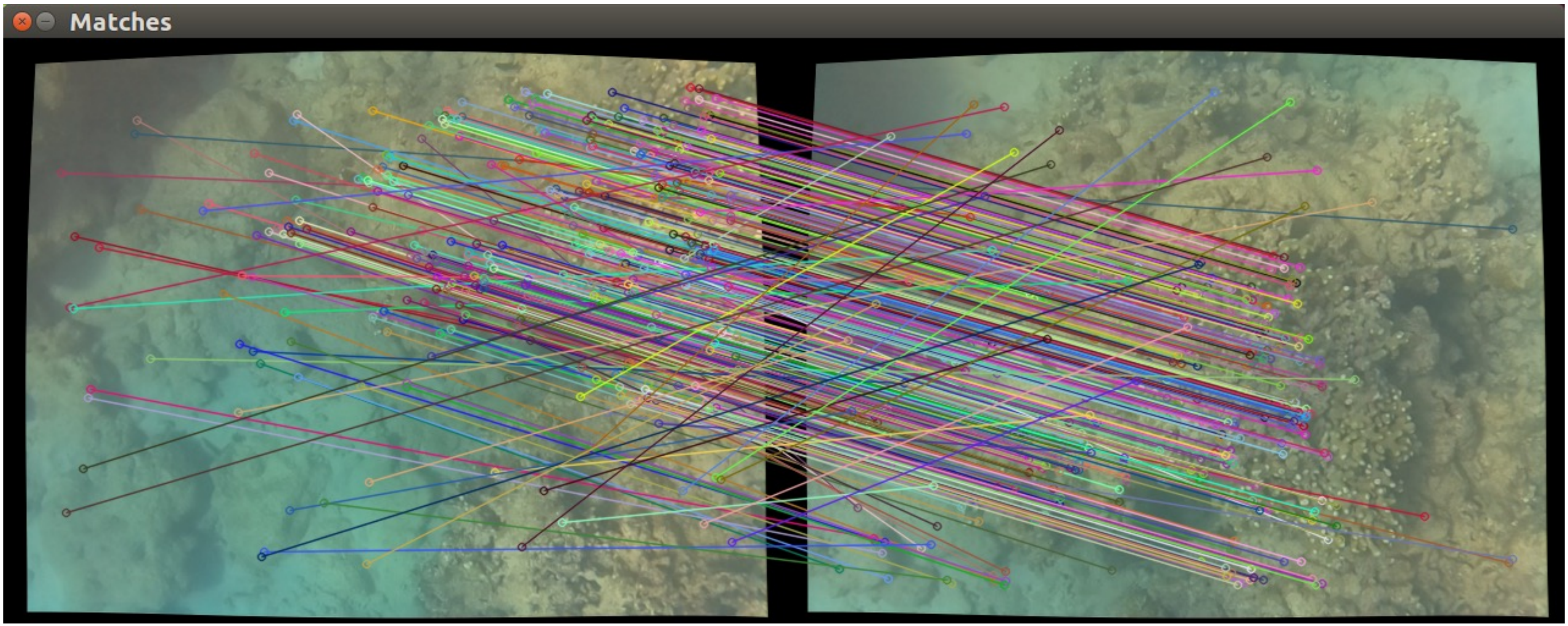
Good Feature

- Invariant to transformations
- Unique
- Efficient to compute
- Good precision and high recall
- Several Alternatives:
  – Harris Corners (OpenCV)
  – SURF (OpenCV)
  – SIFT
  – ORB
  – etc

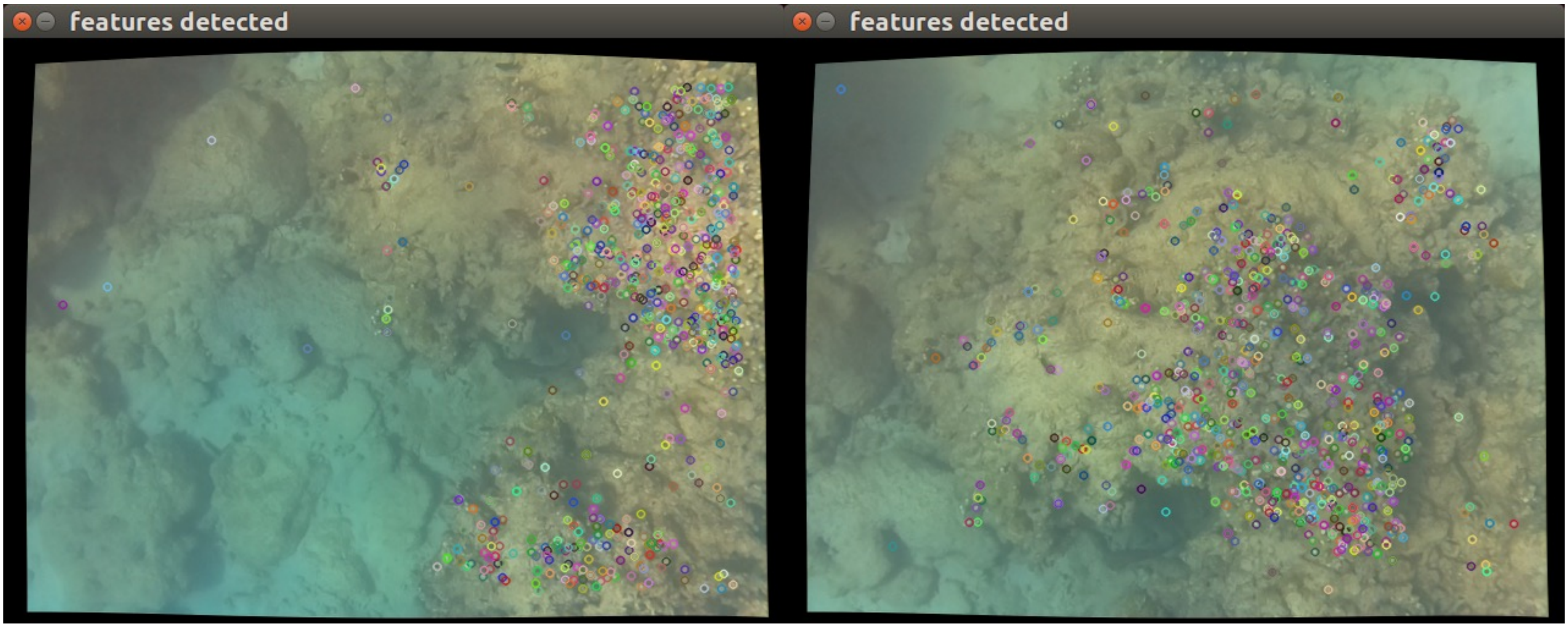
Harris Corners



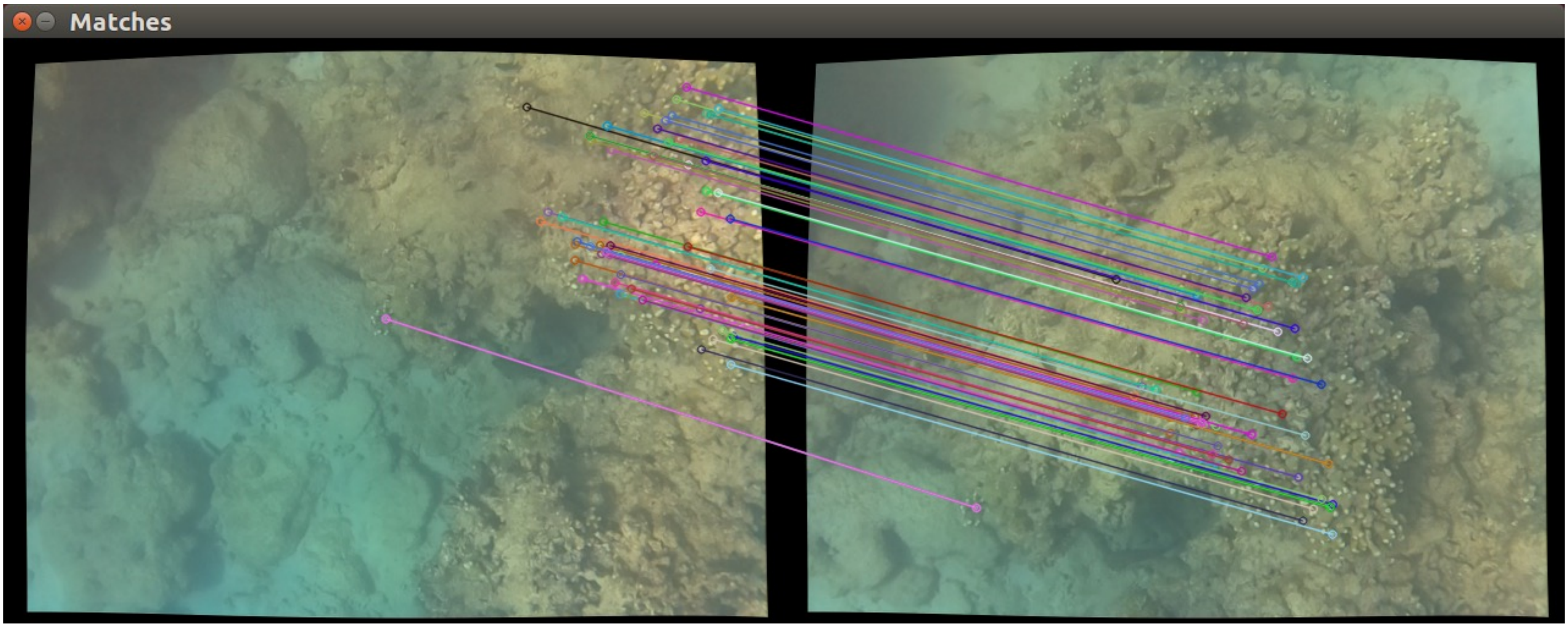
Harris Corners



SIFT

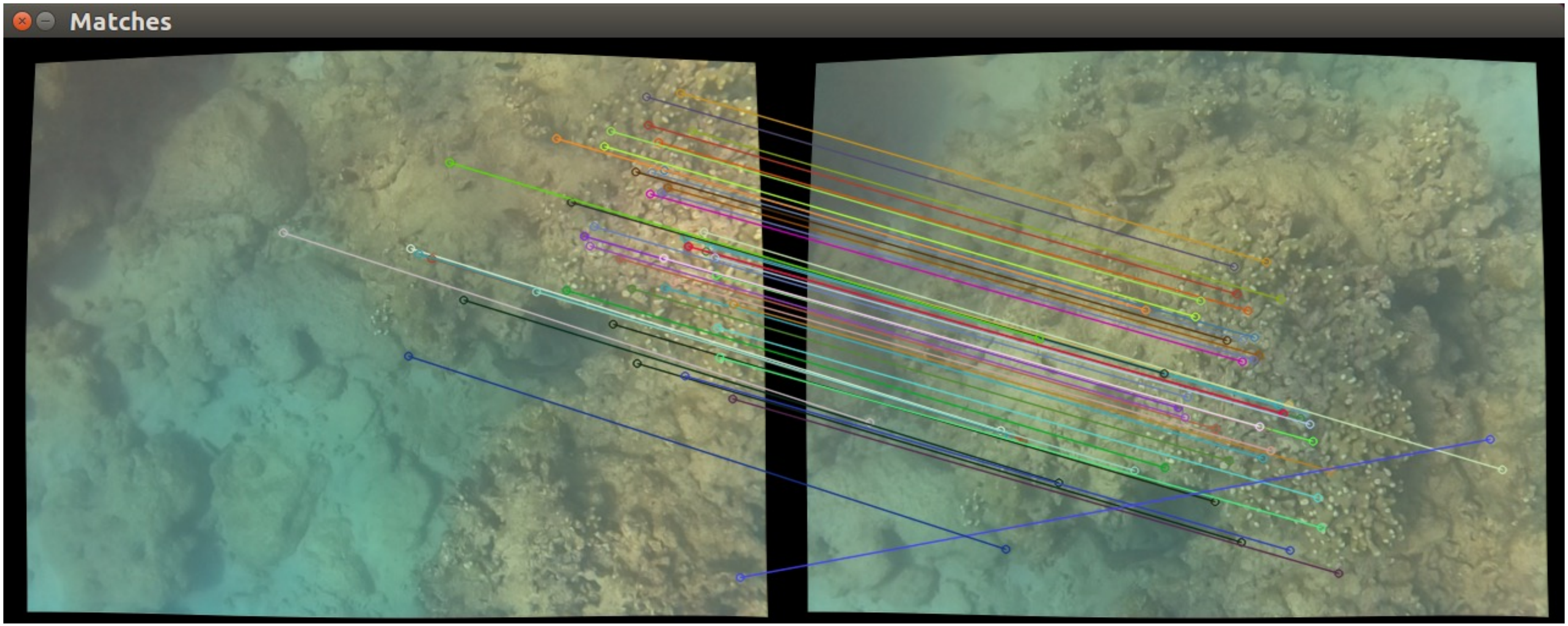


SIFT

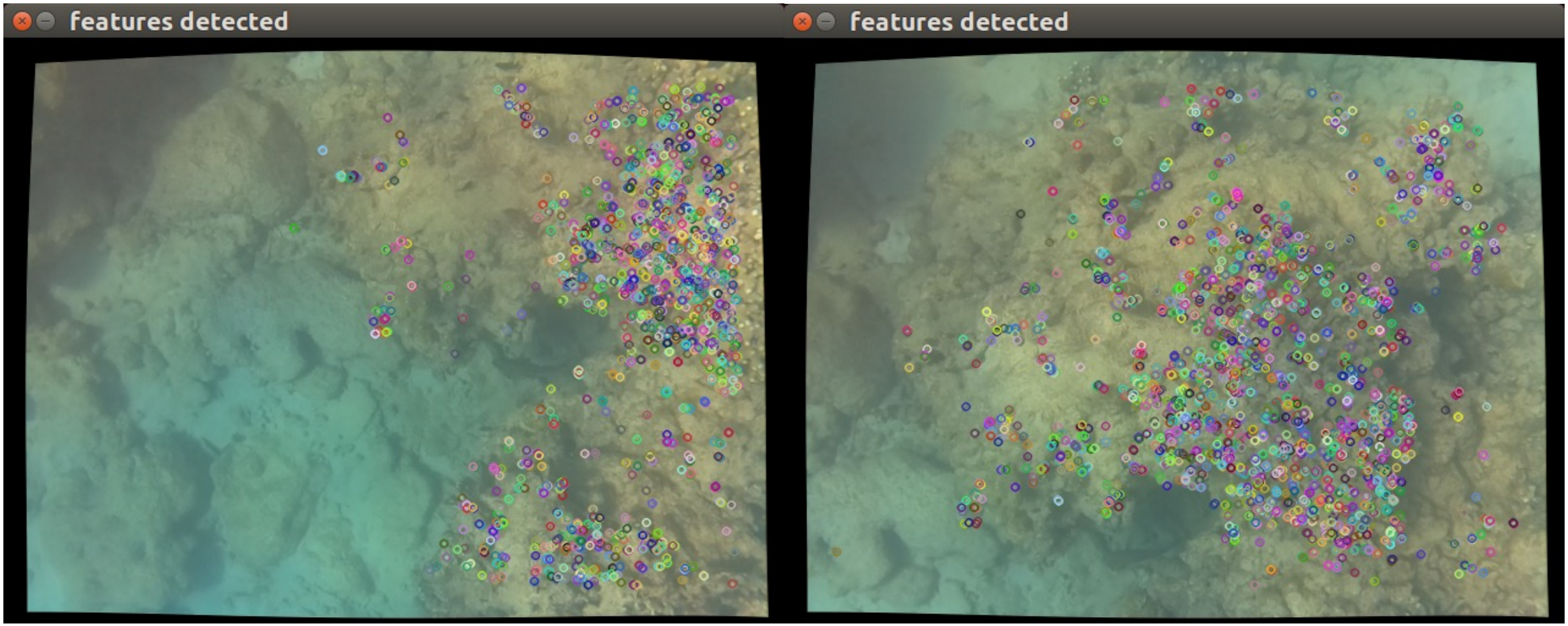


SURF

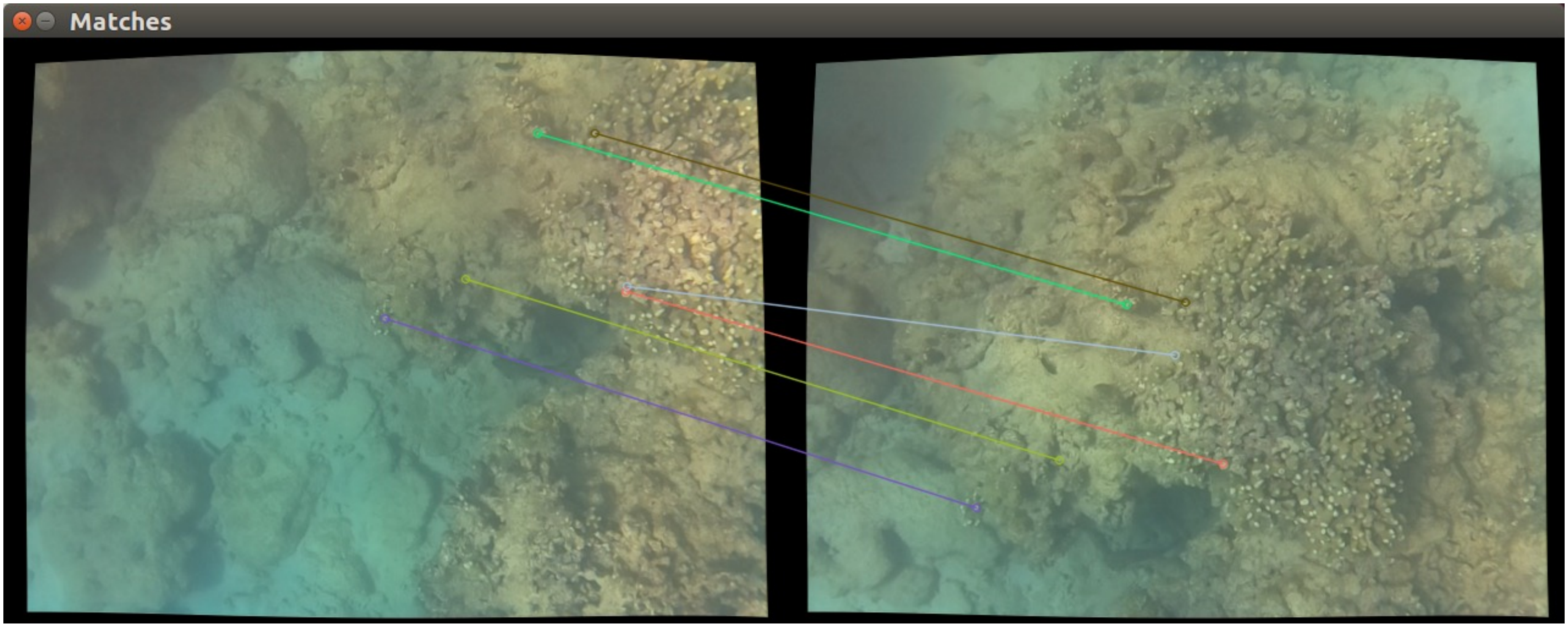
SURF



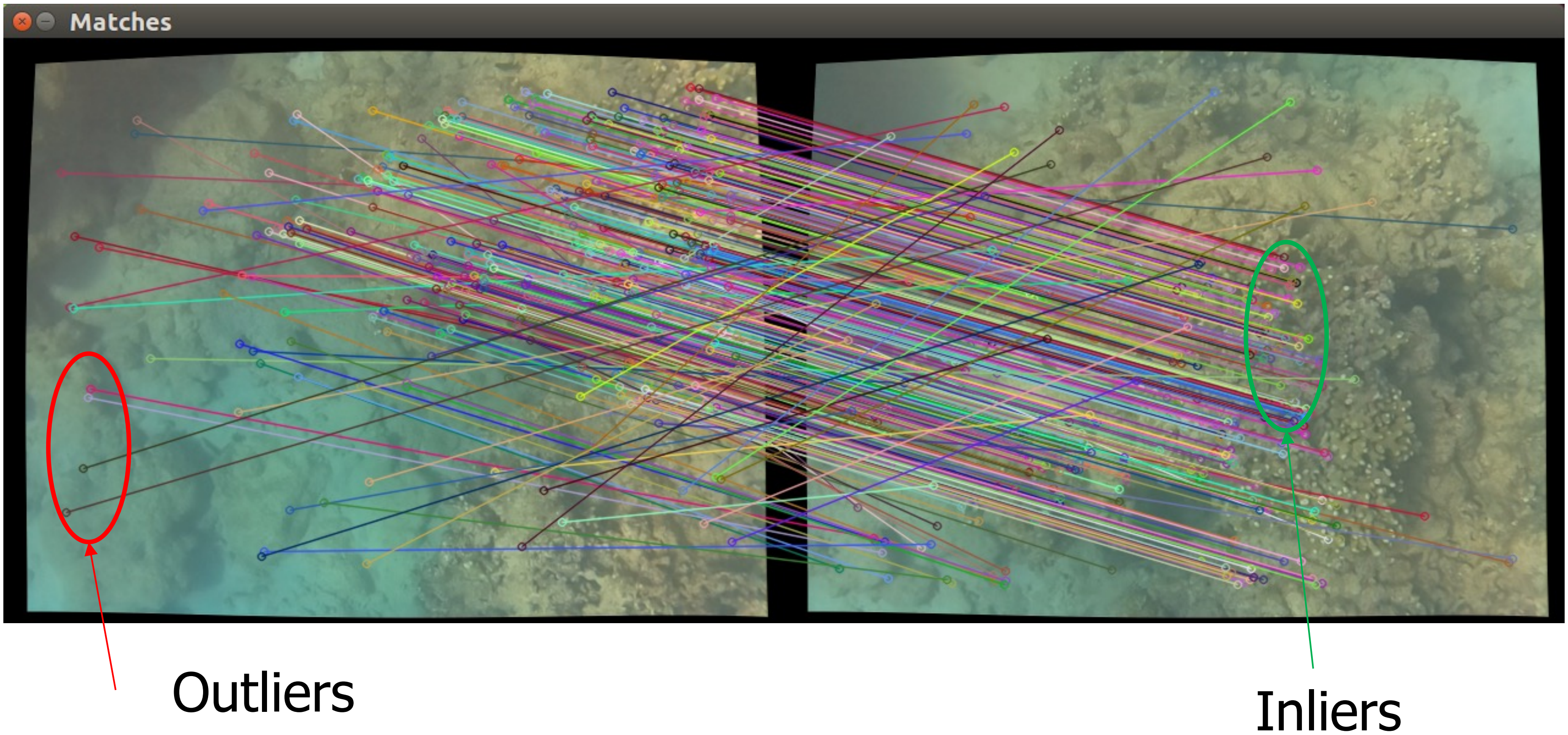
ORB



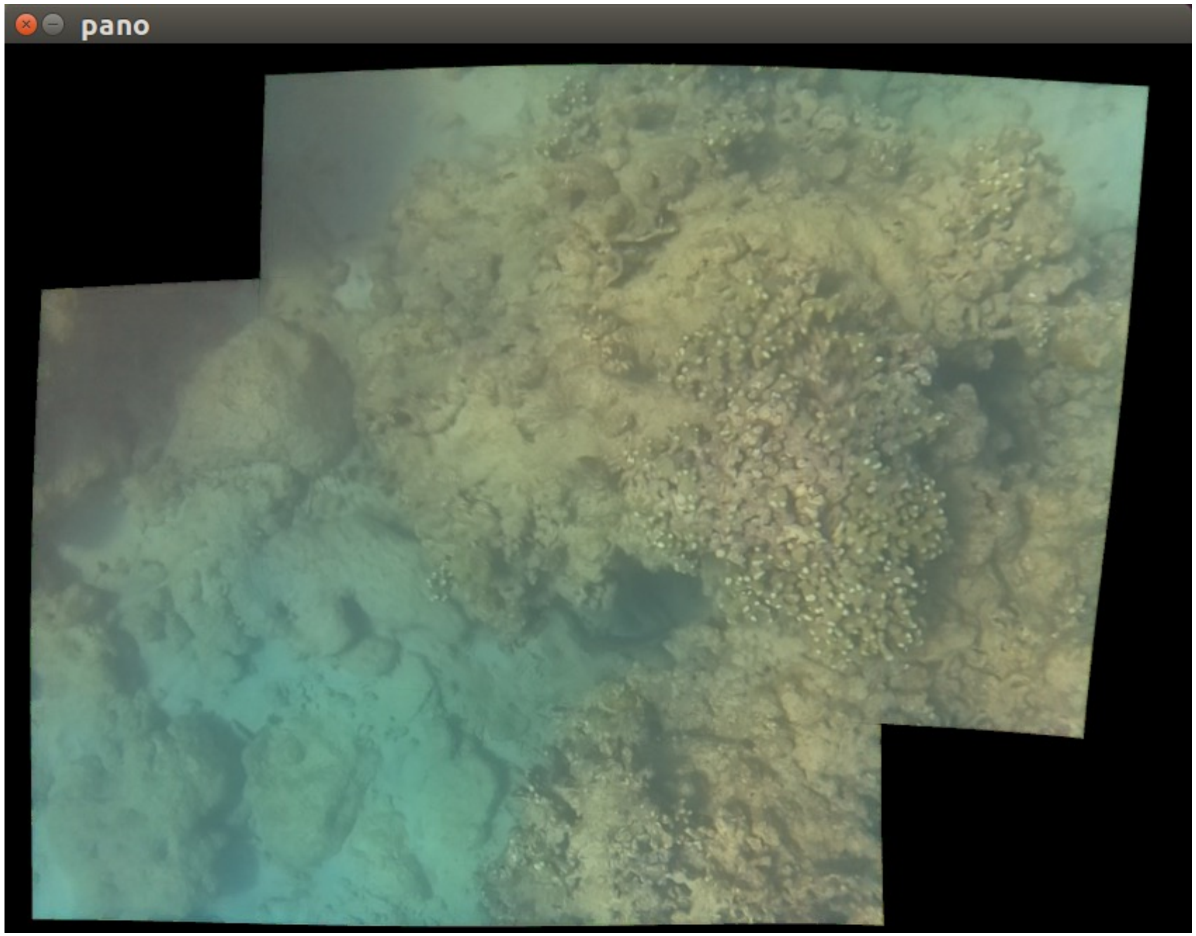
ORB



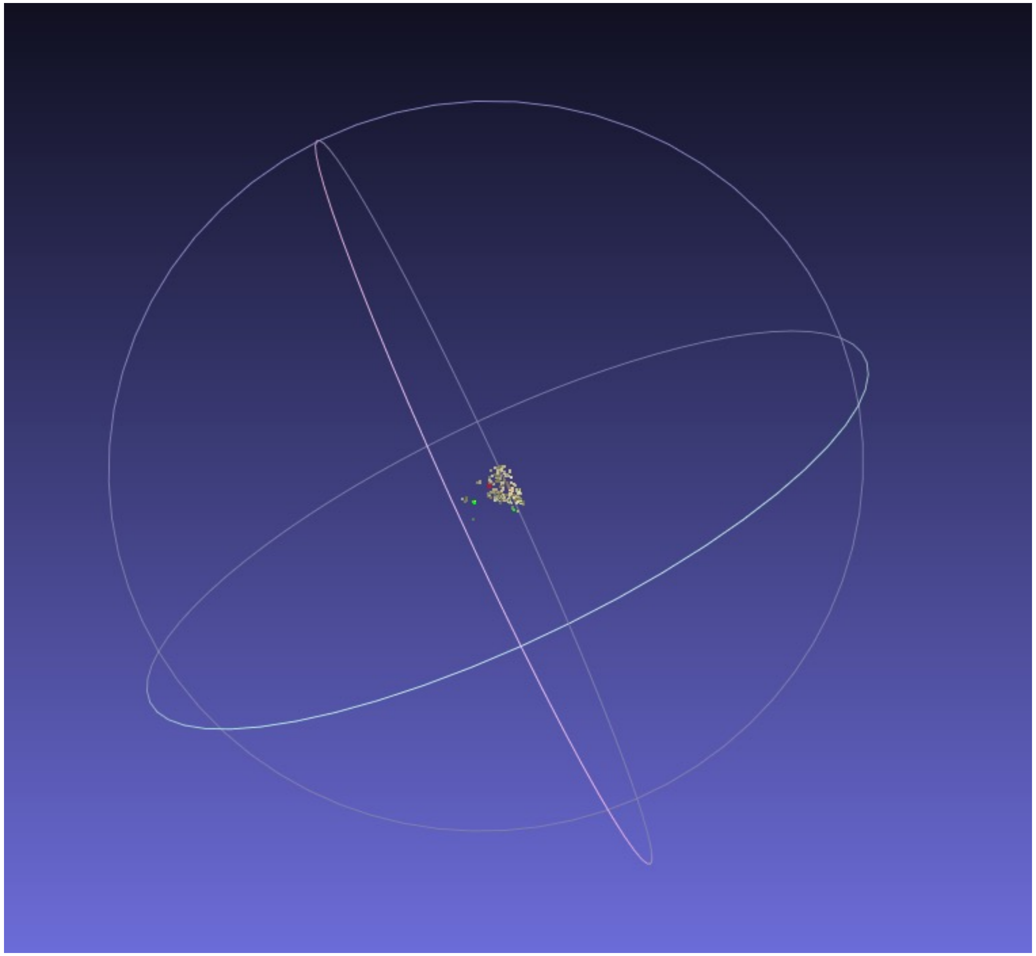
Outliers



Mosaic



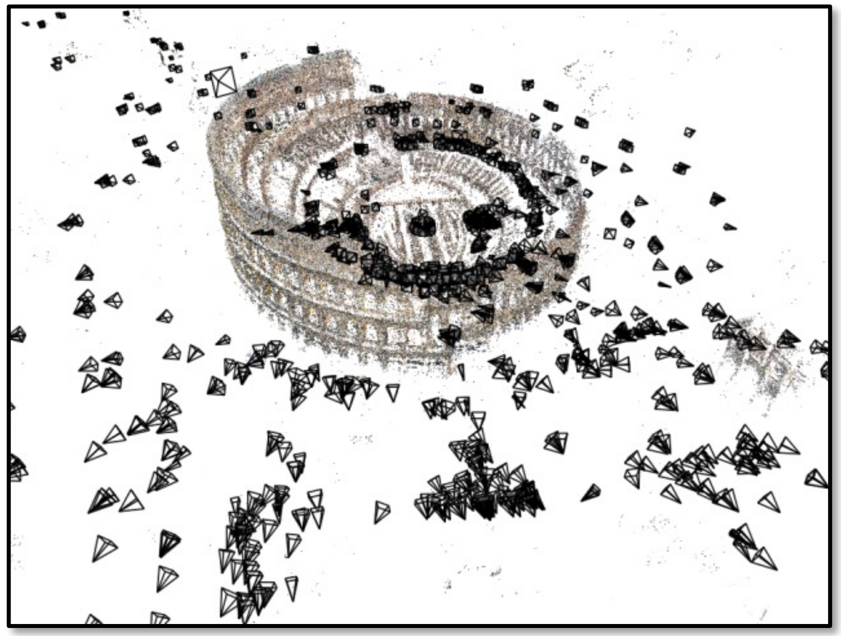
3D Sparse reconstruction



3D Sparse reconstruction

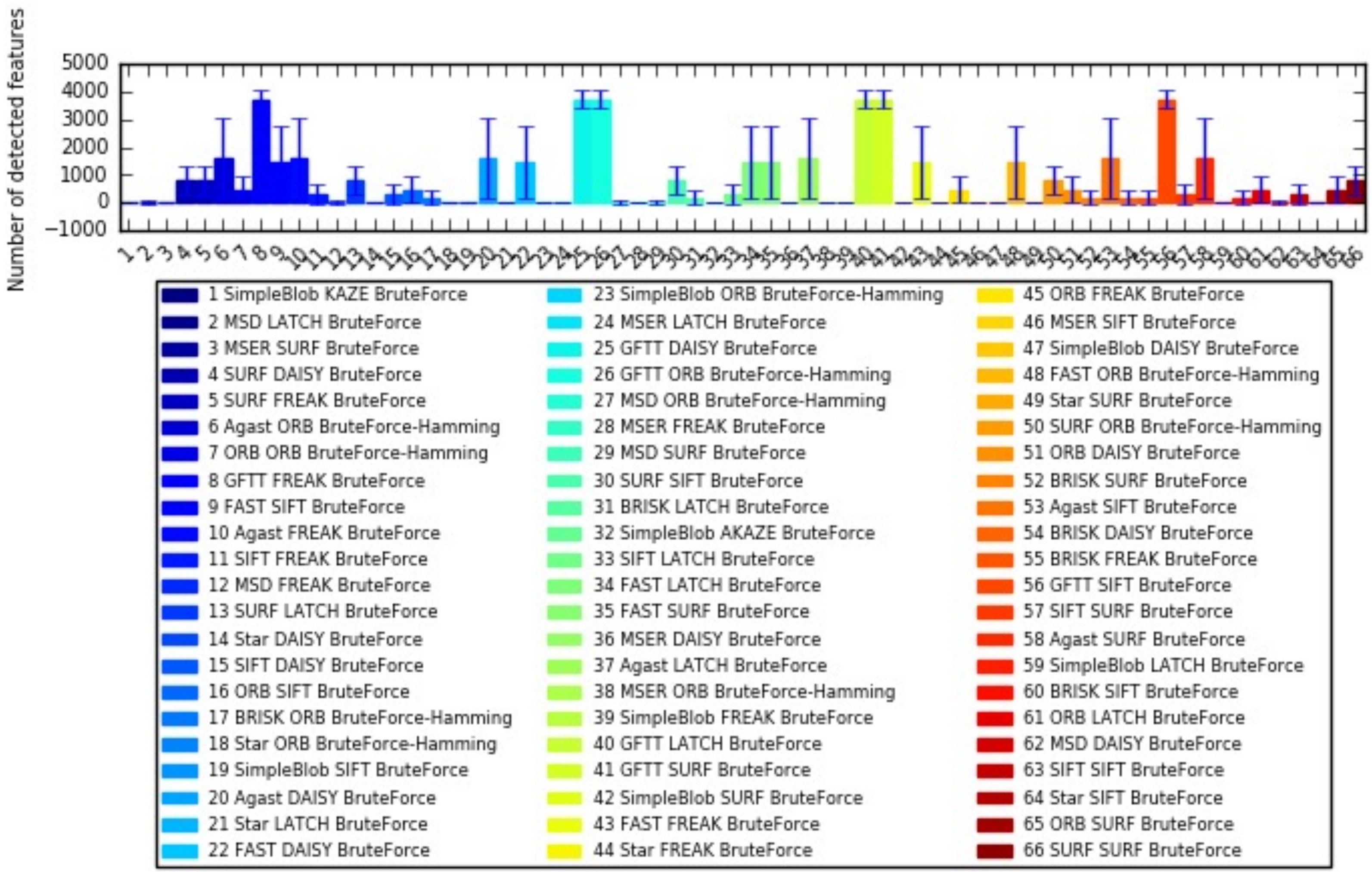
Source: https://grail.cs.washington.edu/rome/

Internet Photos ("Colosseum")

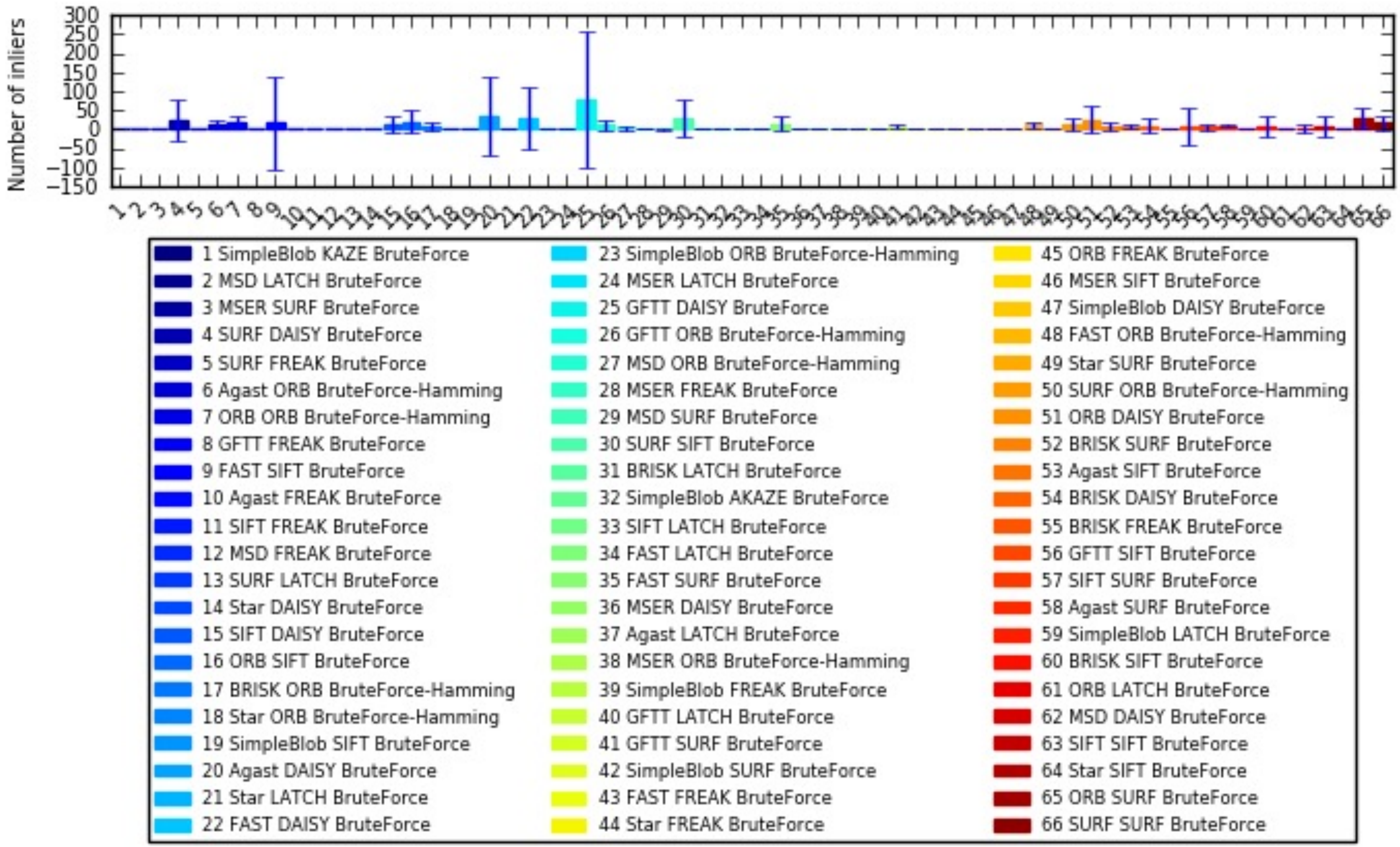


Reconstructed 3D cameras and points

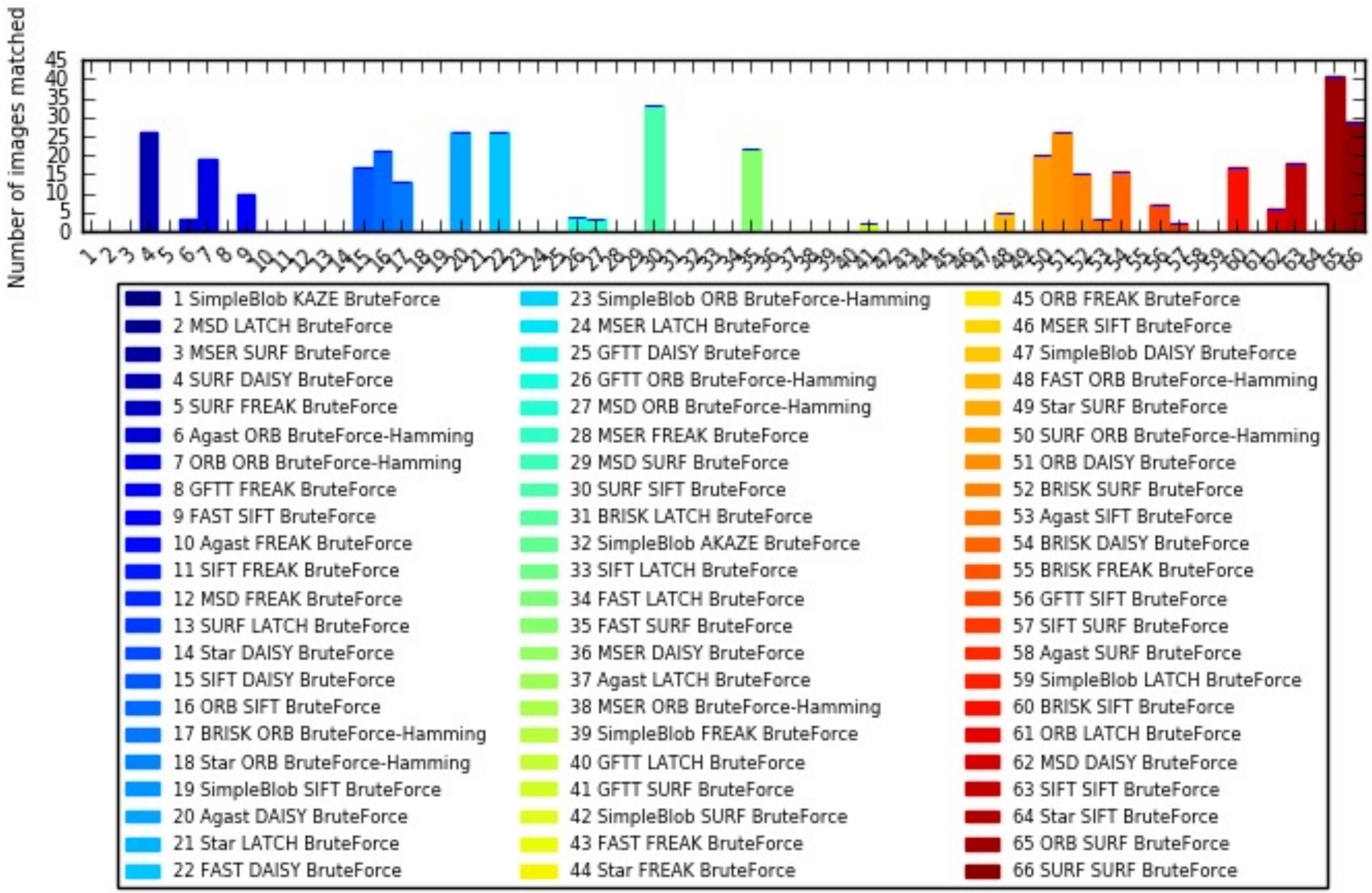
Feature quality



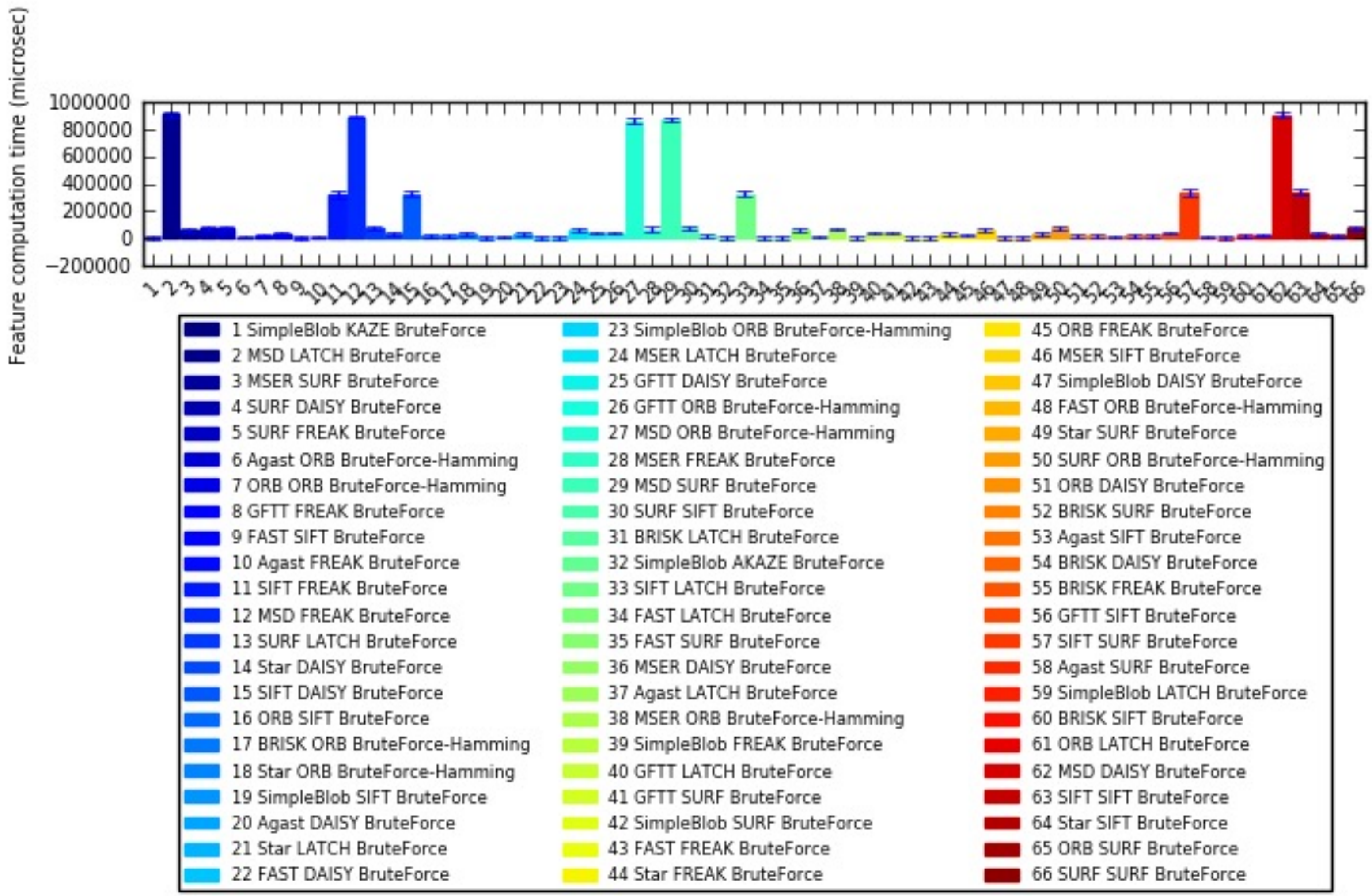
Feature quality



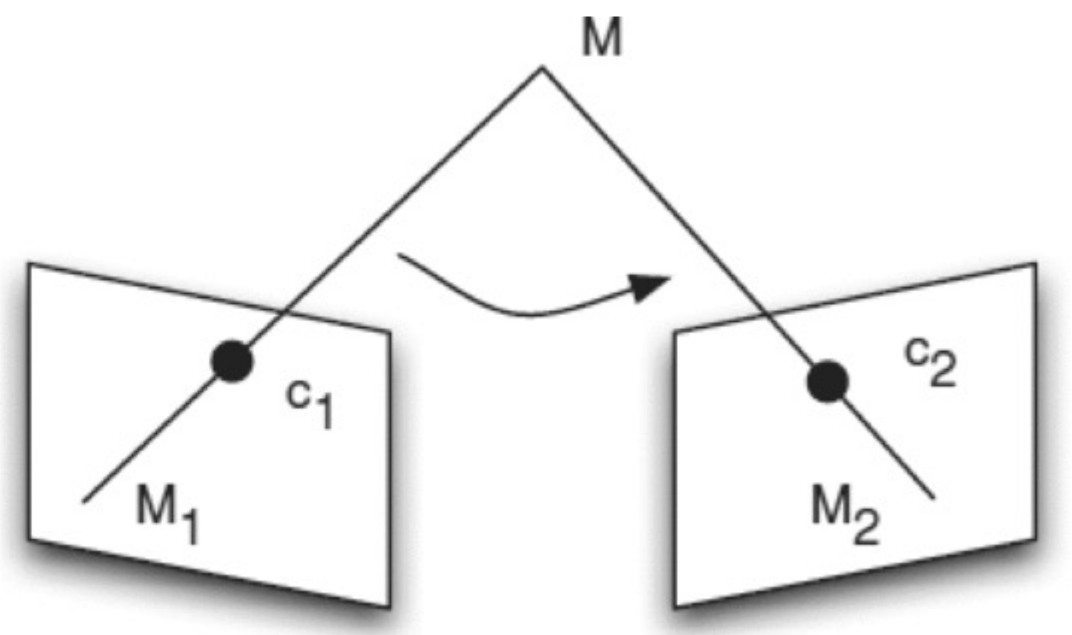
Feature quality



Feature quality



Egomotion



$$C_1 M_1 (T \times R C_2 M_2) = 0$$

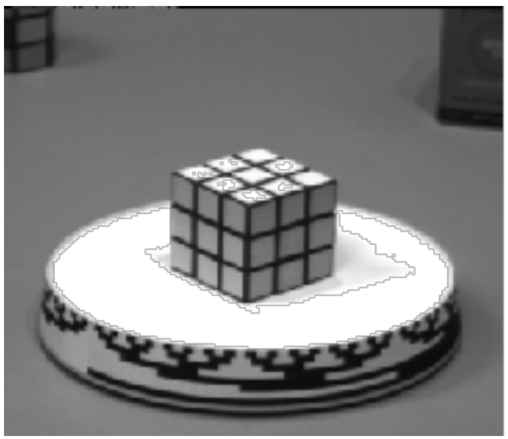
Visual Odometry/Structure from Motion

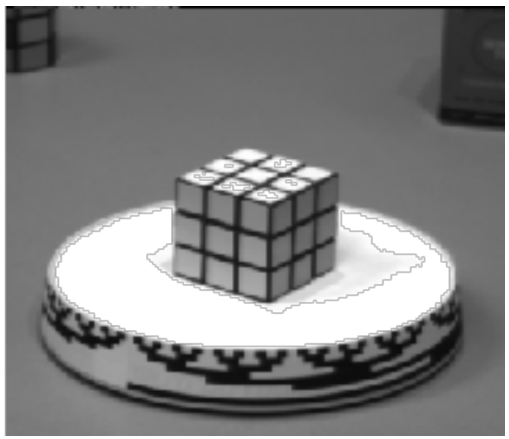
Image stream → Feature detection → Feature matching (tracking) → Motion estimation → Optimization

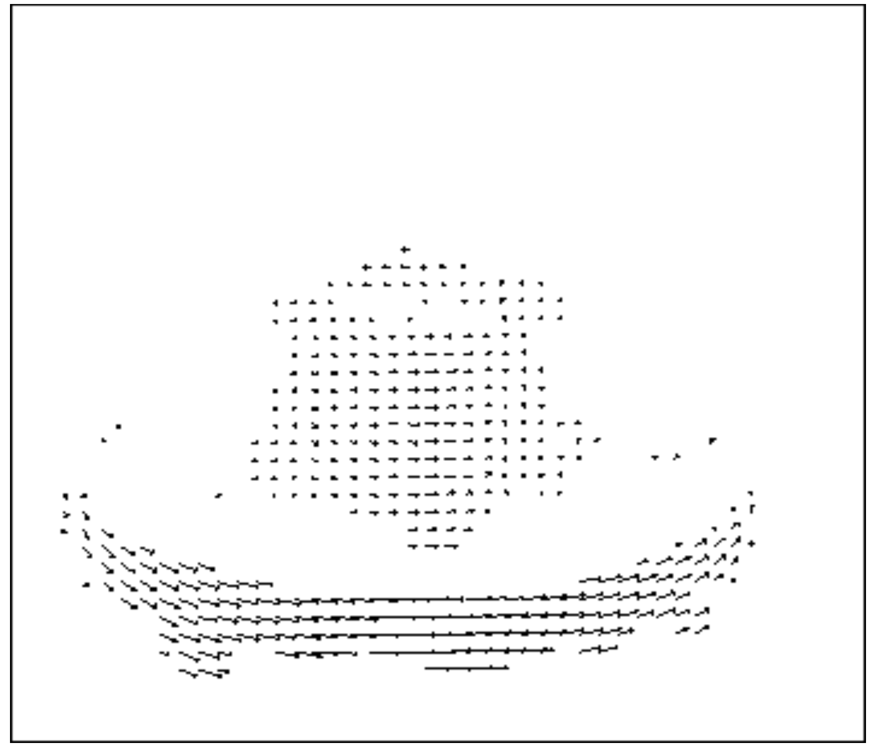
Optical Flow

- Definition:
  - *the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene.*

Optical Flow Field



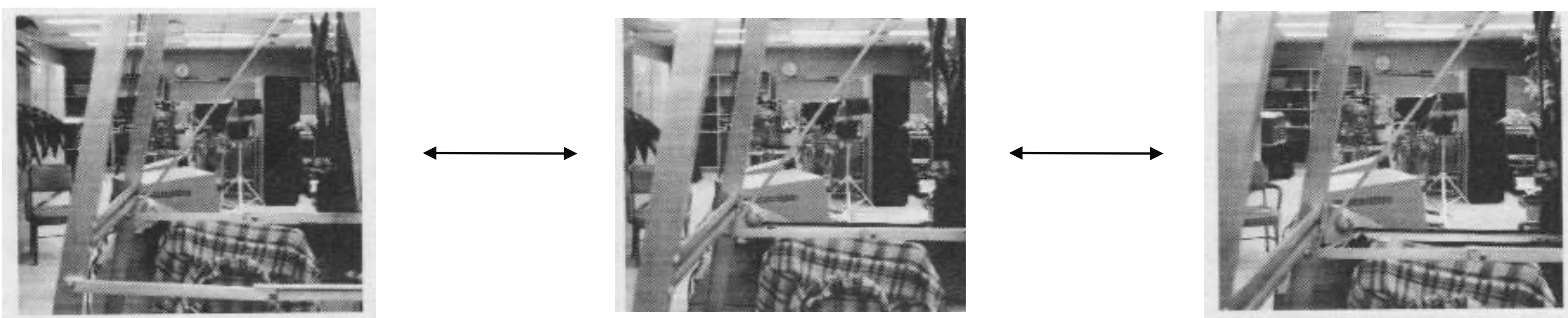




Optical flow

Information about *image motion* rather than the *scene.*
This is a classic ***reconstruction*** *problem.*

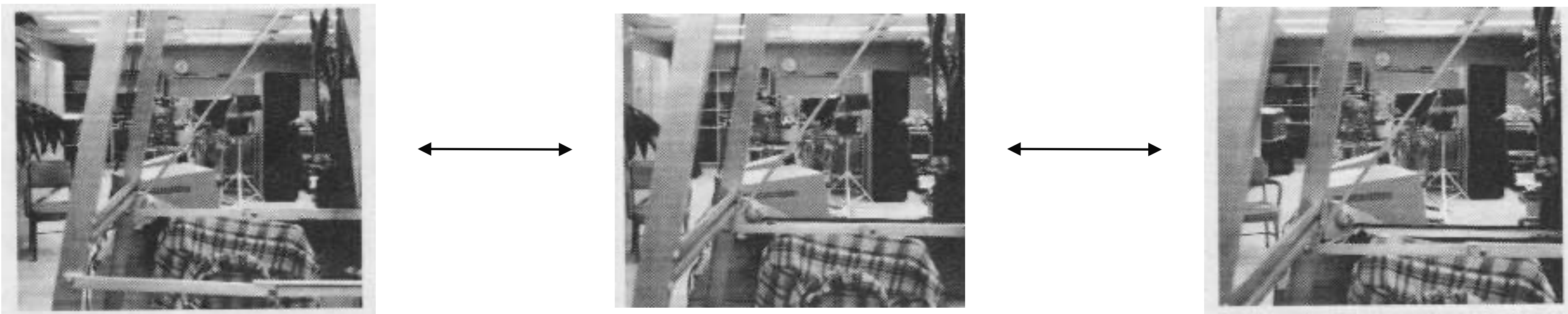
This next step might be to use the image motion to infer scene motion, robot motion or 3D layout.

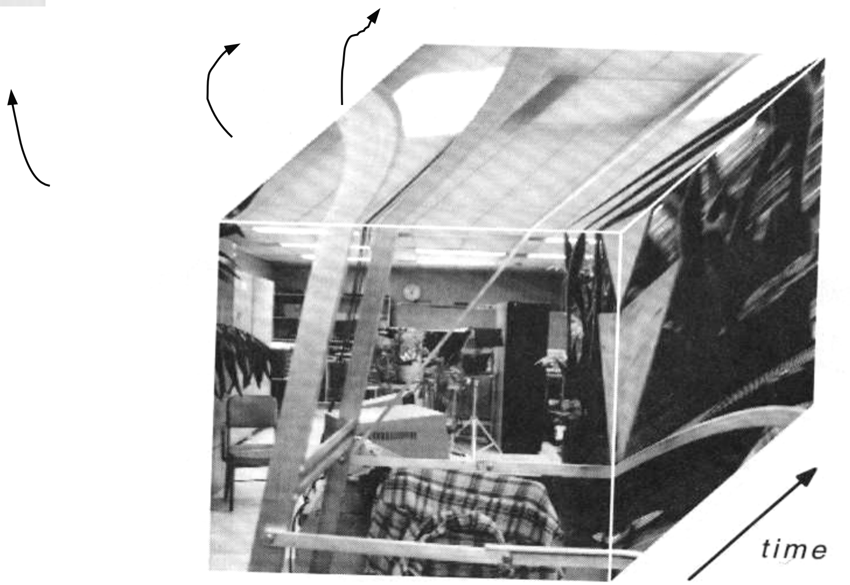


time sequence of images

Optical flow

Information about *scene motion* rather than the *scene.*



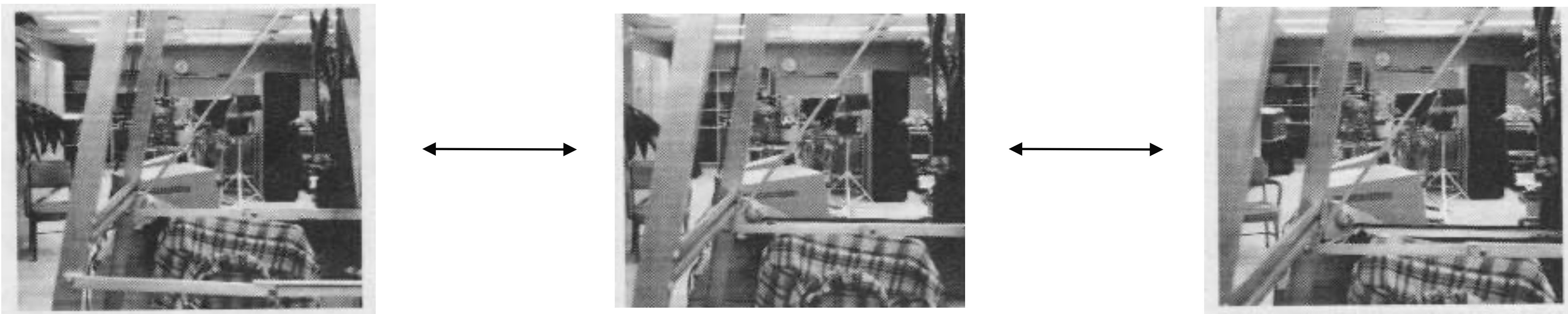


an "image cube"

$I(x,y,t)$

Optical flow

Information about *scene motion* rather than the *scene.*



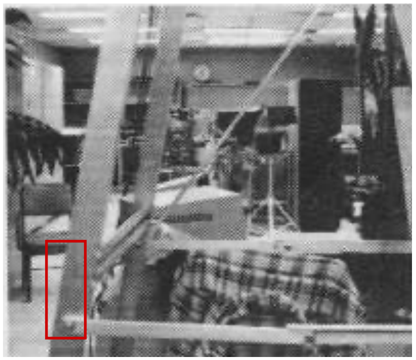
optical flow

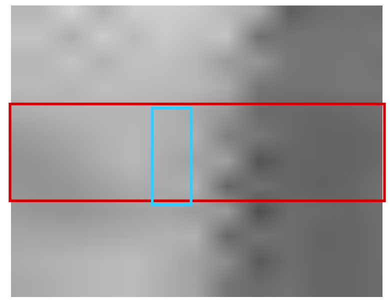
How ?

Optical Flow

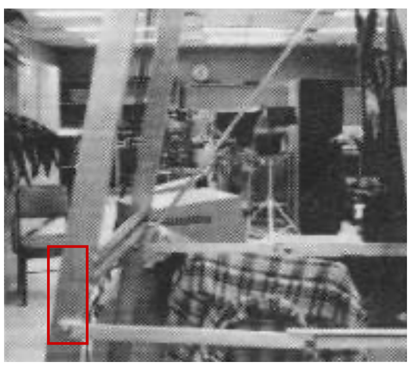
- By measuring the direction that intensities are moving...

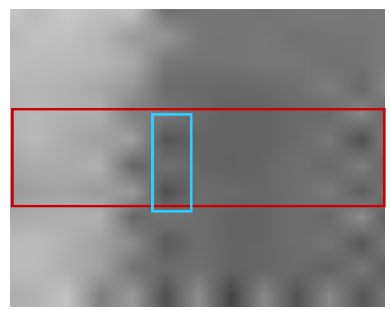
$I(x,y,t)$





99	90	90	70	40
95	90	70	40	40
90	90	70	40	40
90	90	70	40	40
90	70	50	40	30





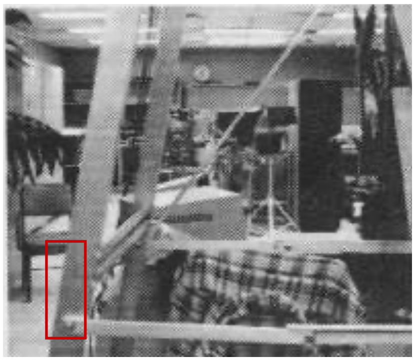
90	90	70	40	25
90	70	40	40	25
90	70	40	40	25
90	70	40	40	20
70	50	40	30	15

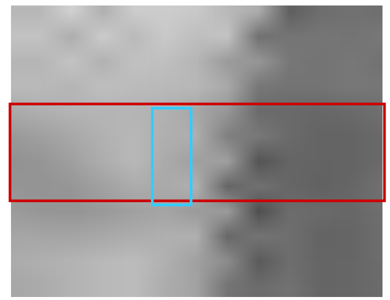
- We can estimate things...

Optical Flow

By measuring the direction that intensities are moving...

I(x,y,t)



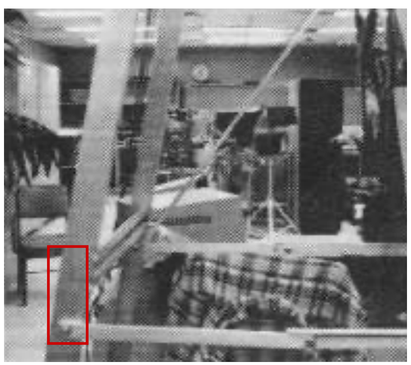


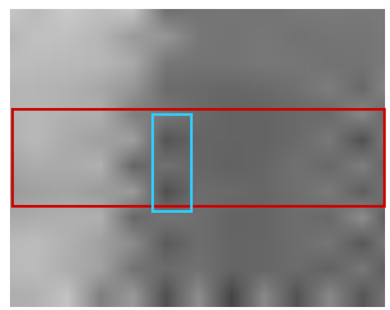
I(x,y,0)

99	90	90	70	40
95	90	70	40	40
90	90	**70**	40	40
90	90	70	40	**40**
90	70	50	40	30

I(0,0,0)

I(2,-1,0)





I(x,y,1)

90	90	70	40	25
90	70	40	40	25
90	70	**40**	40	25
90	70	40	40	20
70	50	40	30	15

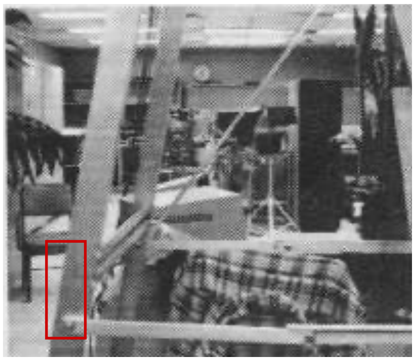
I(0,0,1)

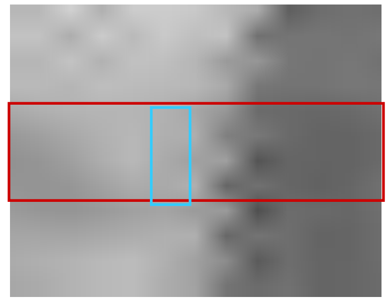
We can estimate things ...

$$\frac{dI}{dx} = I_x \quad \text{at } (0,0,0)$$

Optical Flow

By measuring the direction that intensities are moving...





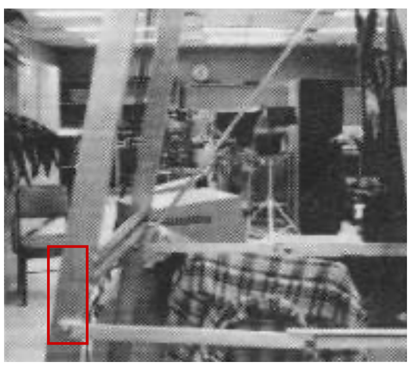
I(x,y,t)

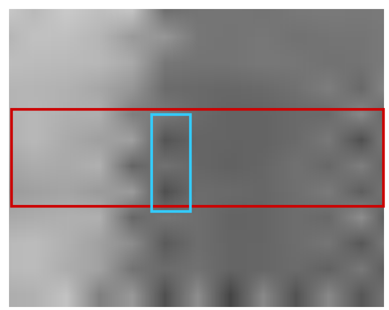
I(x,y,0)

99	90	90	70	40
95	90	70	40	40
90	90	70	40	40
90	90	70	40	**40**
90	70	50	40	30

I(0,0,0)

I(2,-1,0)





I(x,y,1)

90	90	70	40	25
90	70	40	40	25
90	70	40	40	25
90	70	40	40	20
70	50	40	30	15

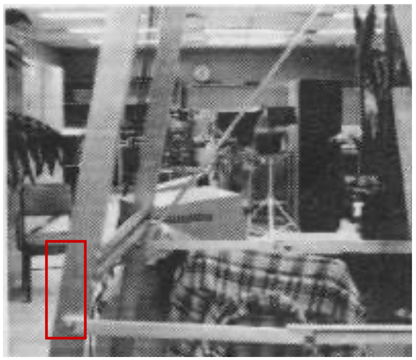
I(0,0,1)

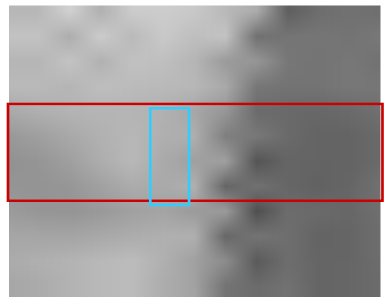
We can estimate things like $\frac{dI}{dx} = I_x$ at (0,0,0) $= \frac{\Delta I}{\Delta x} = \frac{I(1,0,0) - I(0,0,0)}{1 - 0} = -30$

Optical Flow

By measuring the direction that intensities are moving...

I(x,y,t)



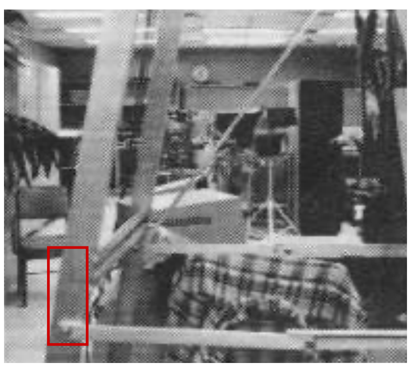


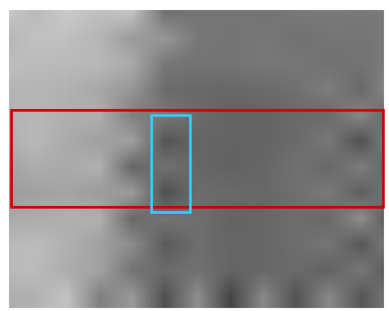
I(x,y,0)

99	90	90	70	40
95	90	70	40	40
90	90	**70**	40	40
90	90	70	40	**40**
90	70	50	40	30

I(0,0,0)

I(2,-1,0)





I(x,y,1)

90	90	70	40	25
90	70	40	40	25
90	70	**40**	40	25
90	70	40	40	20
70	50	40	30	15

I(0,0,1)

We can estimate things like $\frac{dI}{dx} = I_x$ $\frac{dI}{dy} = I_y$ $\frac{dI}{dt} = I_t$ so...

Measuring Optical Flow

Let I(x,y,t) be the sequence of images.

Simplest assumption (constant brightness constraint):

I(x,y,t) = I(x + dx, y + dy, t + dt)

(x,y,t)

99	90	90	70	40
95	90	70	40	40
90	90	70	40	40
90	90	70	40	40
90	70	50	40	30

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90	70	50	40	30

Simplest assumption (constant brightness constraint):

$$I(x,y,t) = I(x + dx, y + dy, t + dt)$$

Reminder: $f(x + dx) = f(x) + f'(x)\, dx + f''(x)\, dx^2 /2 + \ldots$

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$$I(x,y,t) = I(x,y,t) + I_x\,dx + I_y\,dy + I_t\,dt + \text{2nd deriv. + higher}$$

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Let $I(x,y,t)$ be the sequence of images.

(x,y,t)

99	90	90	70	40
95	90	70	40	40
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$$I(x,y,t) = I(x,y,t) + I_x\, dx + I_y\, dy + I_t\, dt + \underbrace{\text{2nd deriv. + higher}}_{\text{ignore these terms}}$$

$$0 = I_x\, dx + I_y\, dy + I_t\, dt$$

Measuring Optical Flow

Let $I(x,y,t)$ be the sequence of images.

Simplest assumption (constant brightness constraint):

$$I(x,y,t) = I(x + dx, y + dy, t + dt)$$

(x,y,t
)

99	90	90	70	40
95	90	70	40	40
90	90	70	40	40
90	90	70	40	40
90	70	50	40	30

Reminder: $f(x + dx) = f(x) + f'(x)\,dx + f''(x)\,dx^2/2 + \ldots$

$$I(x,y,t) = I(x,y,t) + I_x\,dx + I_y\,dy + I_t\,dt + \underbrace{\text{2nd deriv. + higher}}_{\text{ignore these terms}}$$

$$0 = I_x\,dx + I_y\,dy + I_t\,dt$$

$$-I_t = I_x \frac{dx}{dt} + I_y \frac{dy}{dt}$$

intensity-flow equation

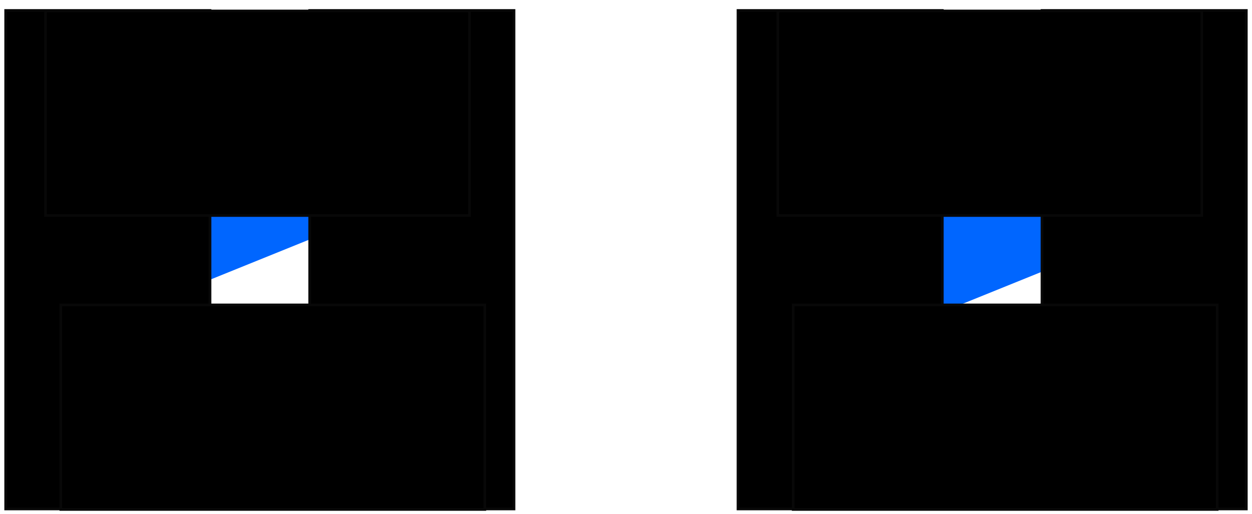
good and bad...

The “aperture” problem

$$-I_t = I_x \frac{dx}{dt} + I_y \frac{dy}{dt}$$

- The intensity-flow equation provides only one constraint on *two* variables (x-motion and y-motion)

$\longrightarrow$ It is only possible to find optical flow in one direction...



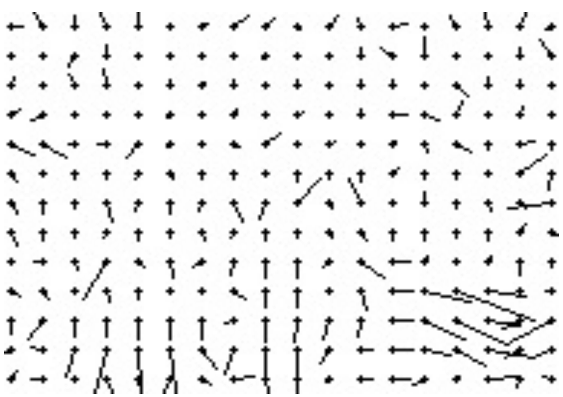
The “aperture” problem

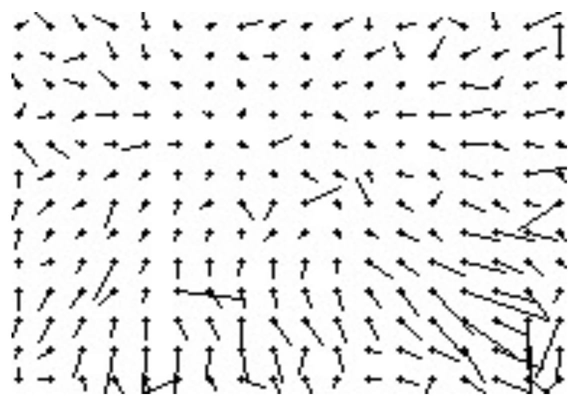
→ It is only possible to find optical flow in one direction...
at any ***single*** *point in the image !*

img1

img2

raw
optical
flow





smoothed
for ten
iterations

Smoothing can be done by incorporating neighboring points’ information.

Observations & Warnings

- Assume the scene itself is static.
- Find matching chunks in the images.
- An instance of *correspondence*.

BUT

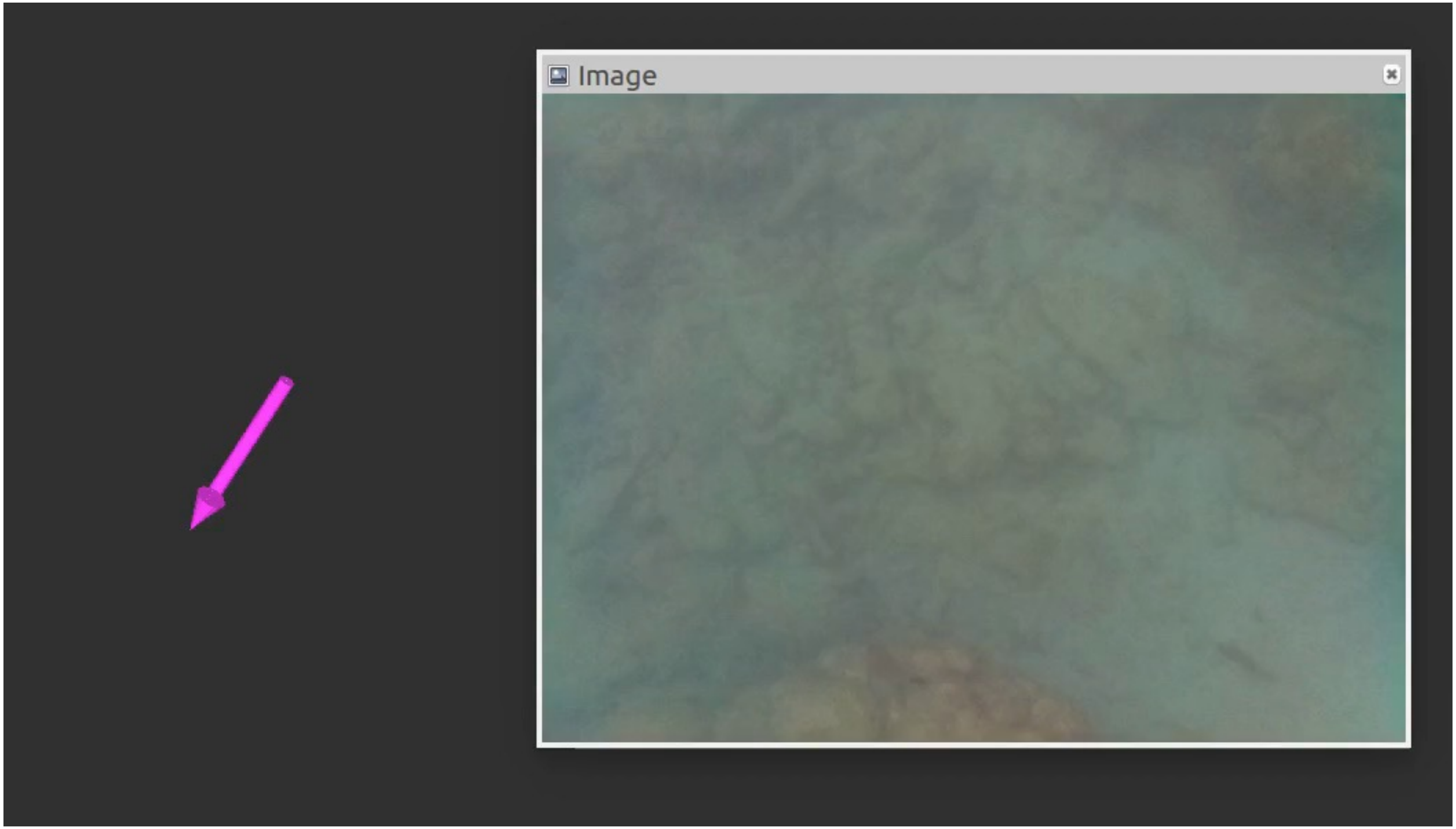
- World really isn't static.
- Lightning might change even in a static scene.

Features vs Optical Flow

- Feature-based methods
  - Detect features (corners, textured areas), extract descriptors, and track them
  - Sparse motion fields, but possibly robust tracking
  - Suitable especially when image motion is large (10s of pixels)
- Direct methods (optical flow)
  - Directly recover image motion from spatio-temporal image brightness variations
  - Global motion parameters directly recovered without an intermediate feature motion calculation
  - Dense motion fields, but more sensitive to appearance variations
  - Suitable for video and when image motion is small (< 10 pixels)

Camera and IMU

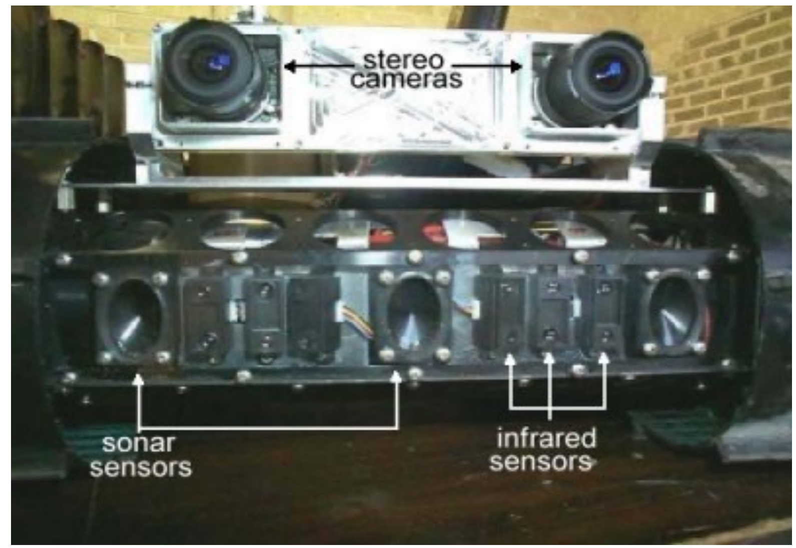
From drifter with Raspberry PI Camera and Pololu MinIMU-9 v3 at Barbados 2016 Field Trials



A Vision “solution”

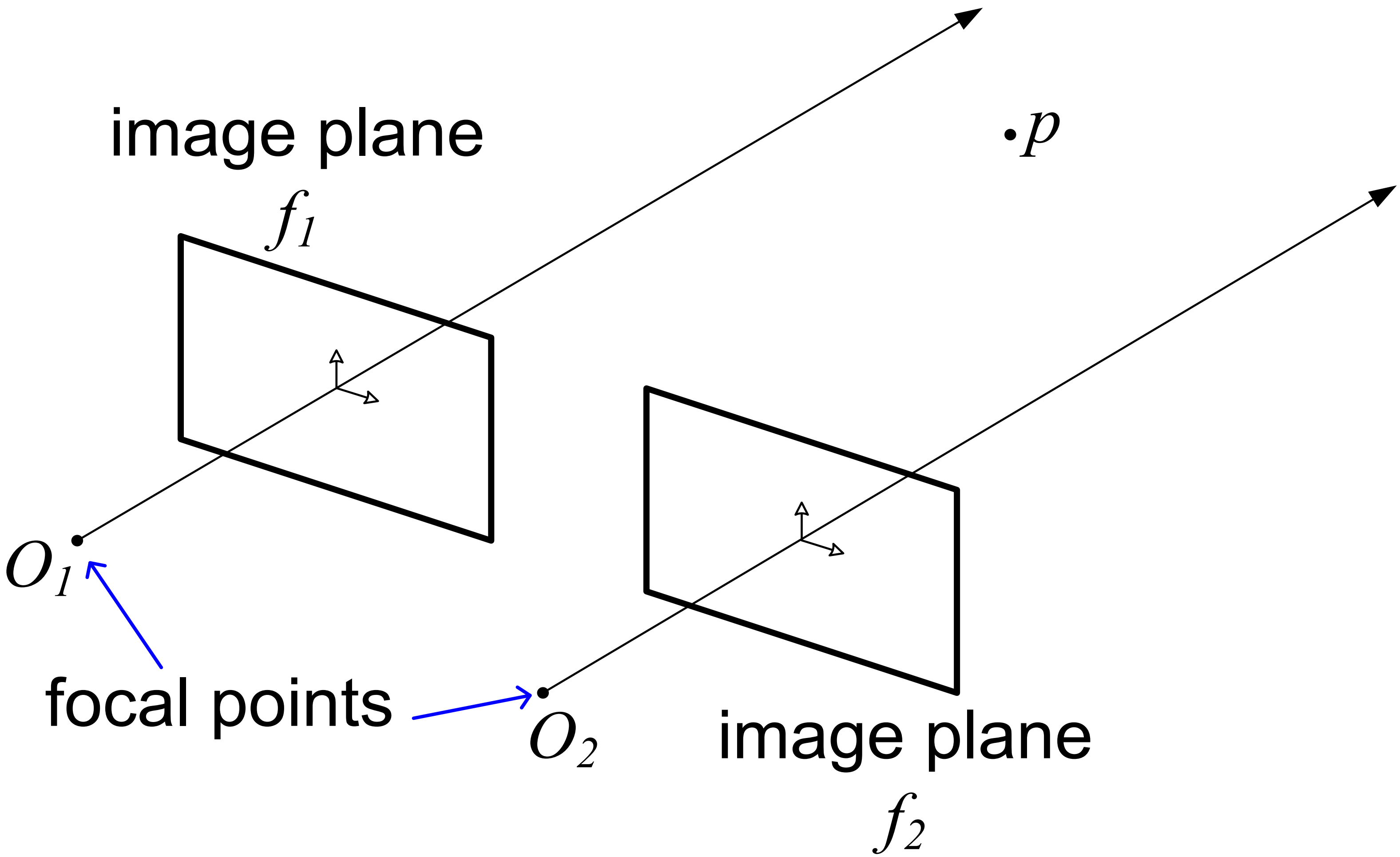
- If interpreting a single image is difficult... What about more ?!

multiple cameras

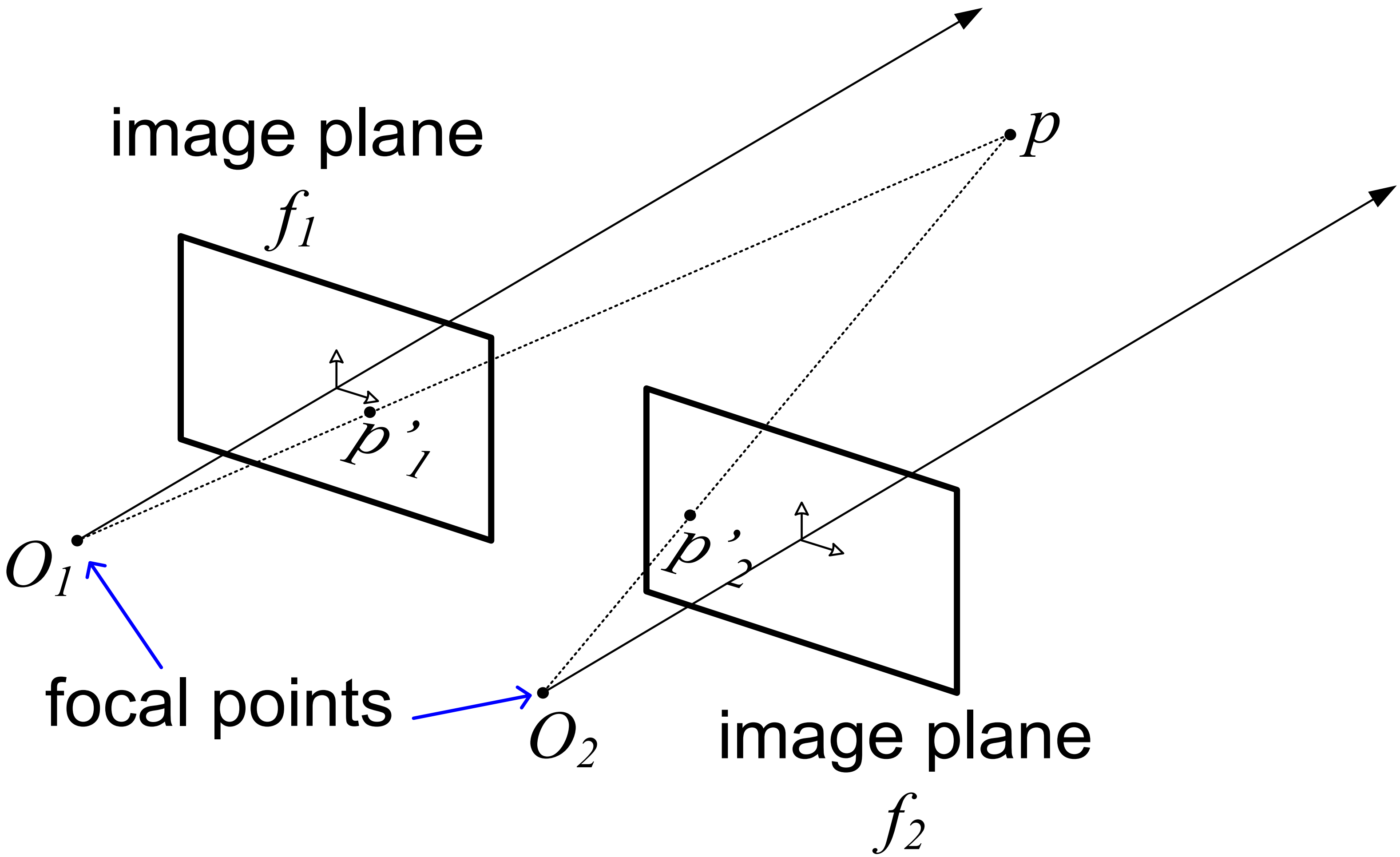


multiple times

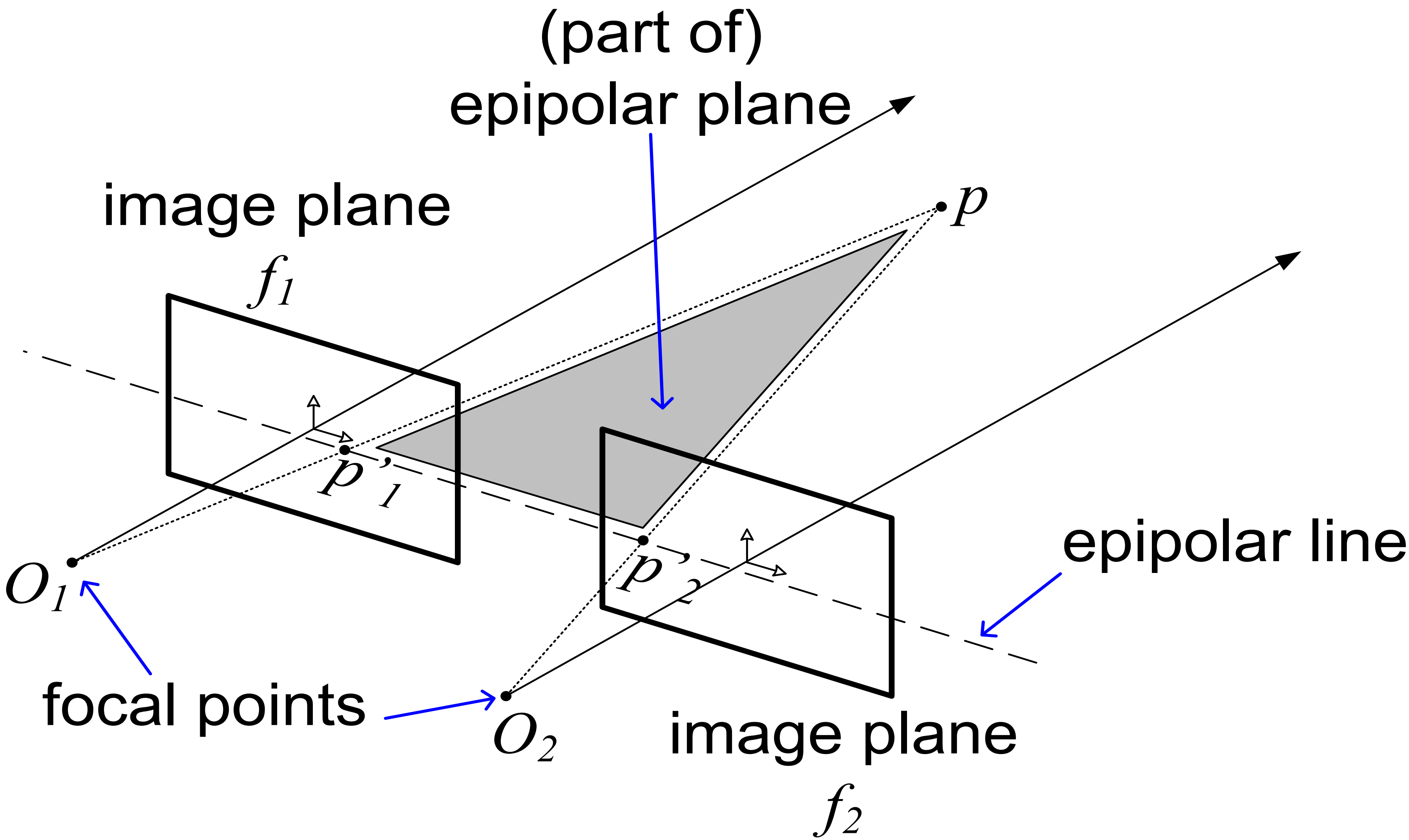
Stereo Vision: Pinhole Camera



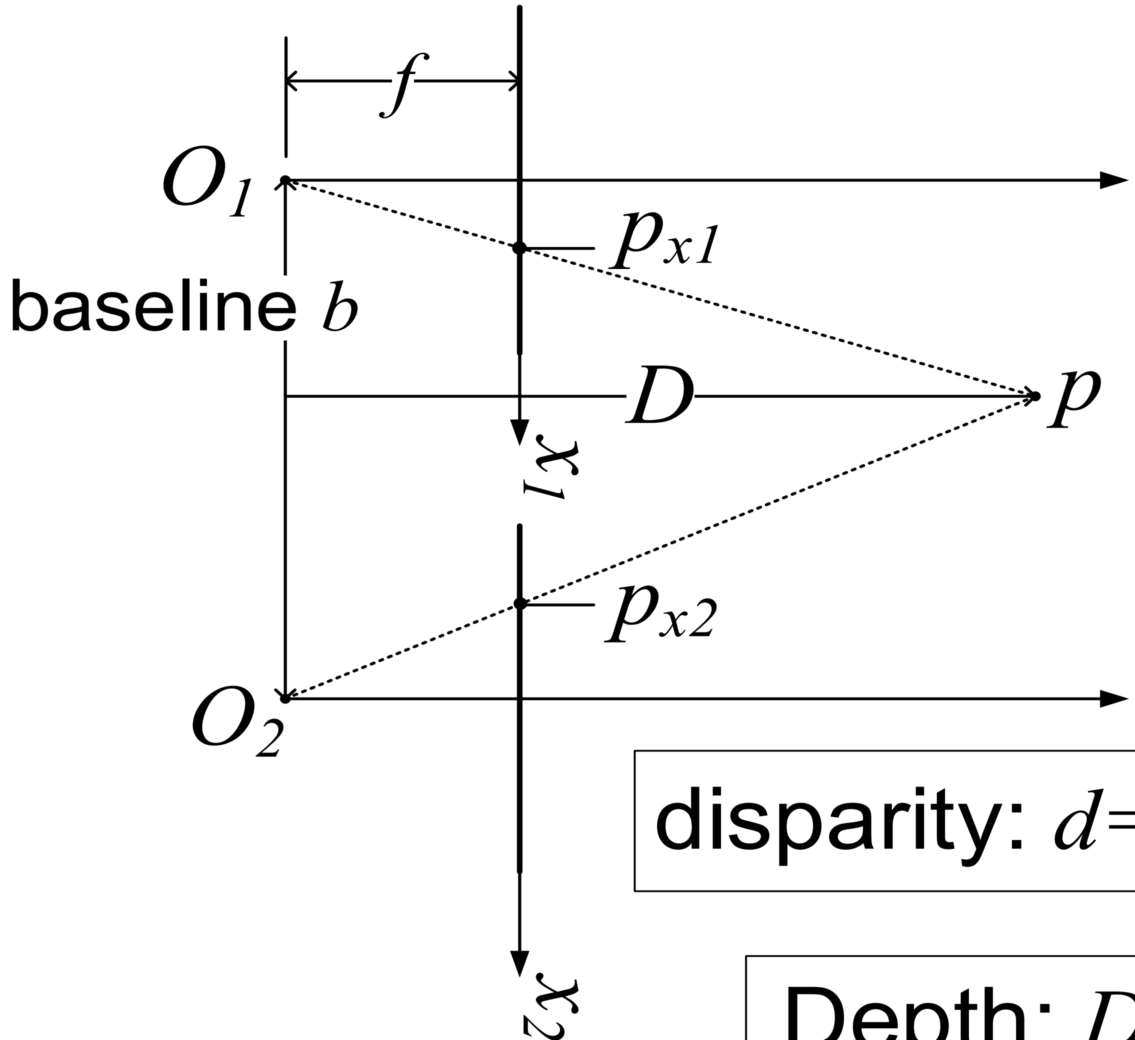
Stereo Vision: Pinhole Camera



Stereo Vision: Pinhole Camera



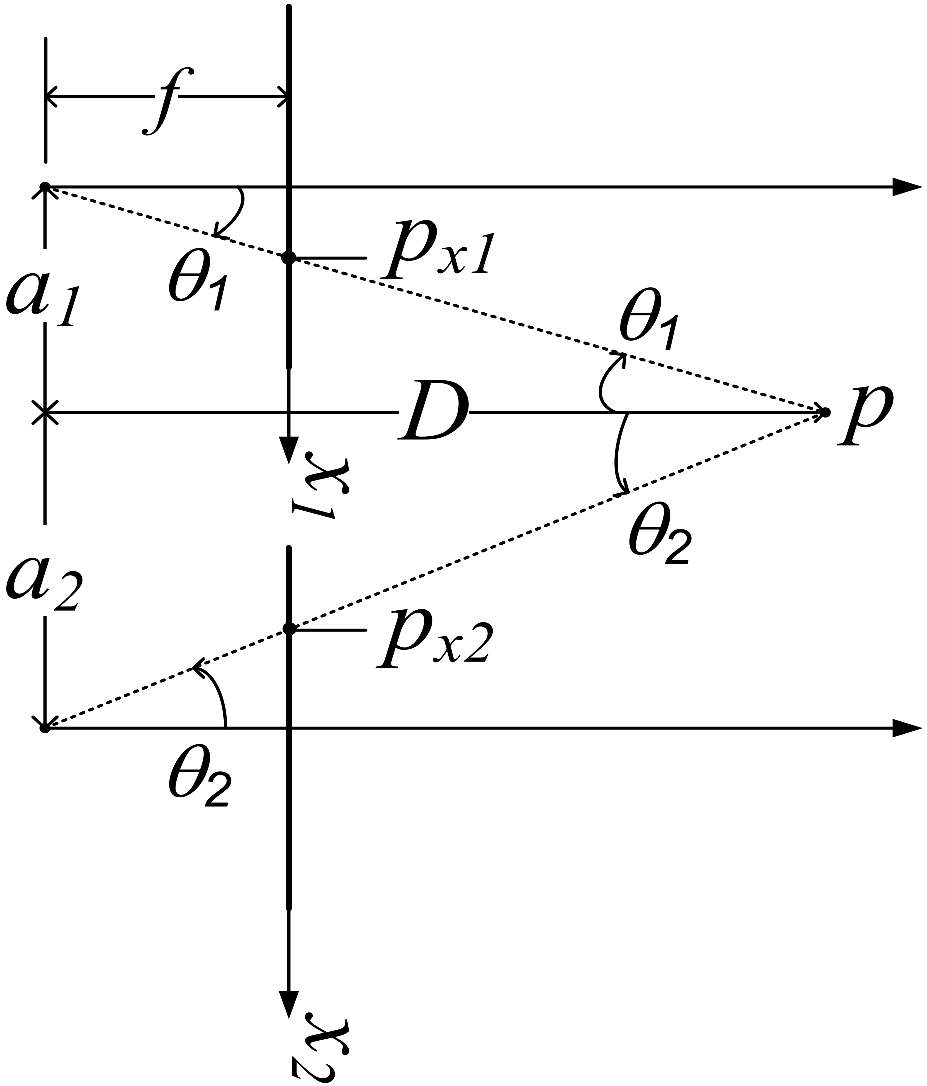
Stereo Vision: Pinhole



disparity: $d = p_{x1} - p_{x2}$

Depth: $D = fb/d$

Stereo Vision: Pinhole

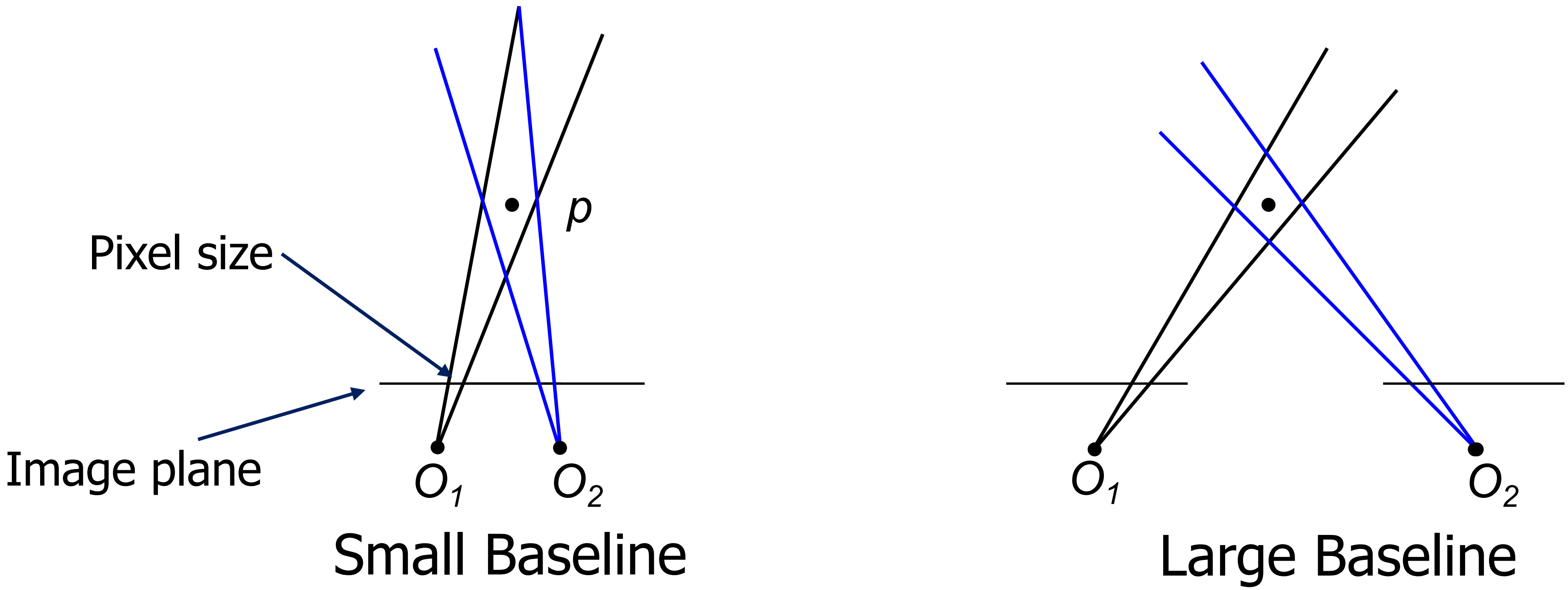


$$\frac{p_{x1}}{f} = \frac{a_1}{D}$$

$$\frac{p_{x2}}{f} = \frac{a_2}{D}$$

$$a_1 + a_2 = b$$

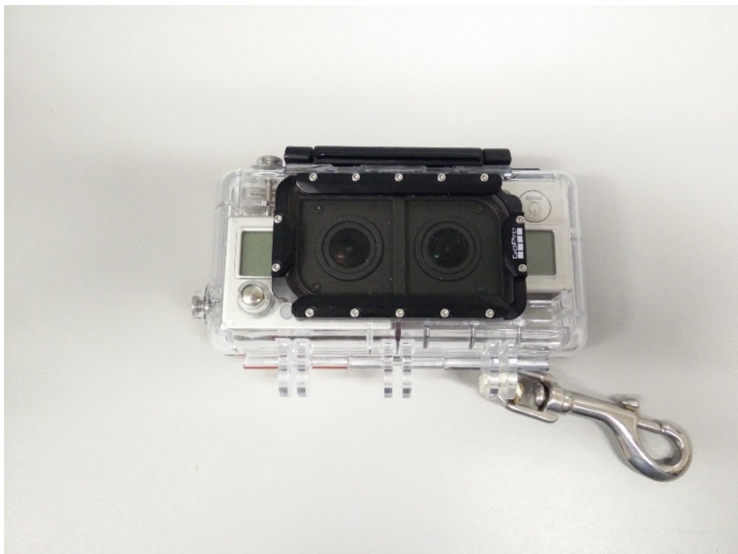
Baseline



- What's the optimal baseline?
  - Too small: large depth error
  - Too large: difficult search problem

Baseline

GoPro 3D HERO System



b=3.2 cm

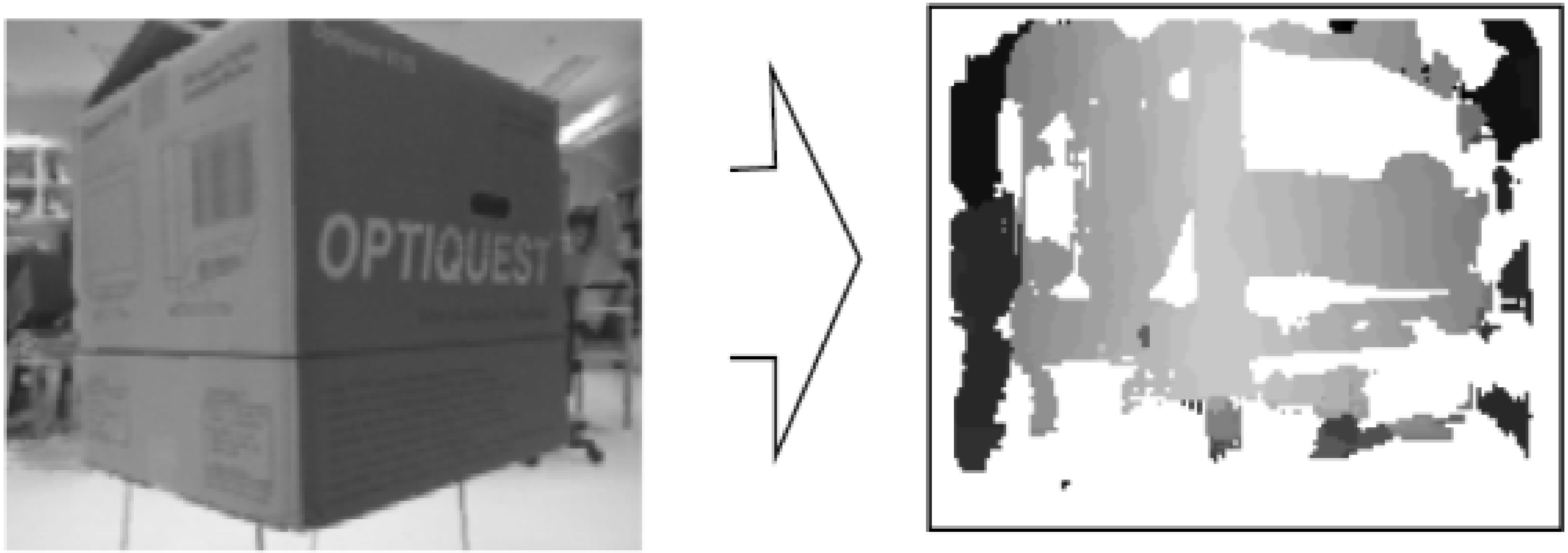
source: http://www.cvlibs.net/datasets/kitti

b=54 cm

Matching Left and Right

3D reconstruction

Stereo: Disparity Map

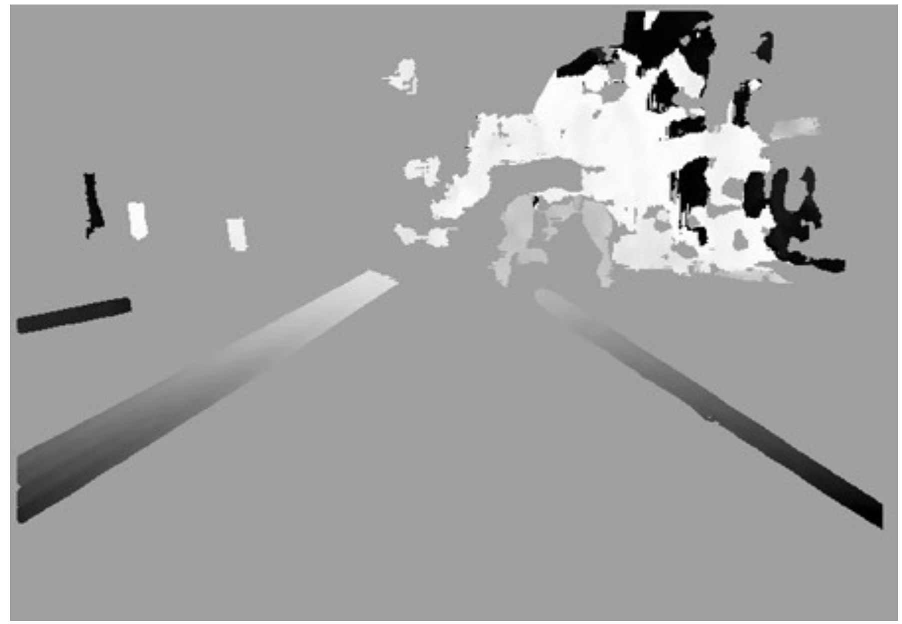


Using real-time stereo vision for mobile robot navigation

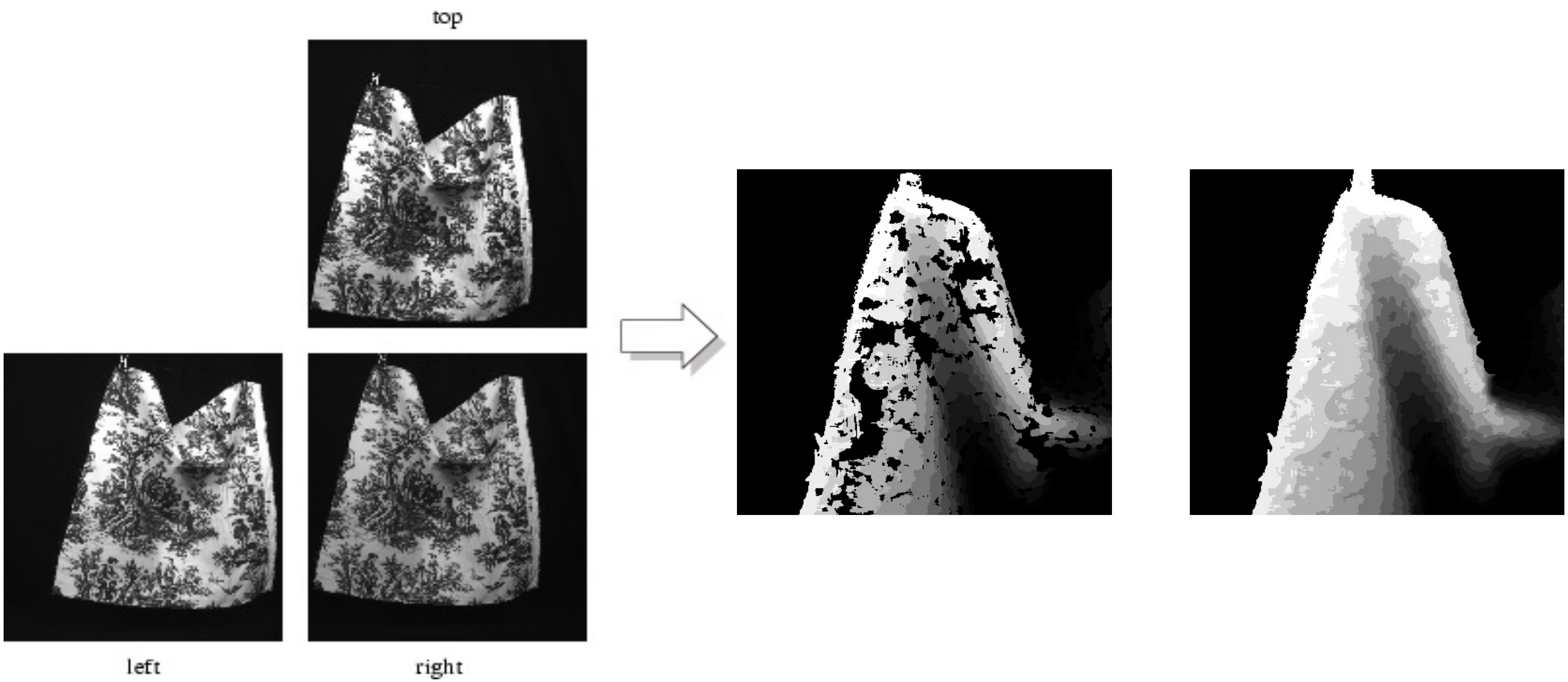
Don Murray Jim Little

Computer Science Dept.
University of British Columbia
Vancouver, BC, Canada V6T 1Z4

Depth Map in a City



Another Example (Hole Filling)



Cloth Parameters and Motion Capture by David Pritchard

B.A.Sc., University of Waterloo, 2001

Stereo Vision

- Large number of algorithms out there:
  http://vision.middlebury.edu/stereo/

  rank 43 different algorithms.

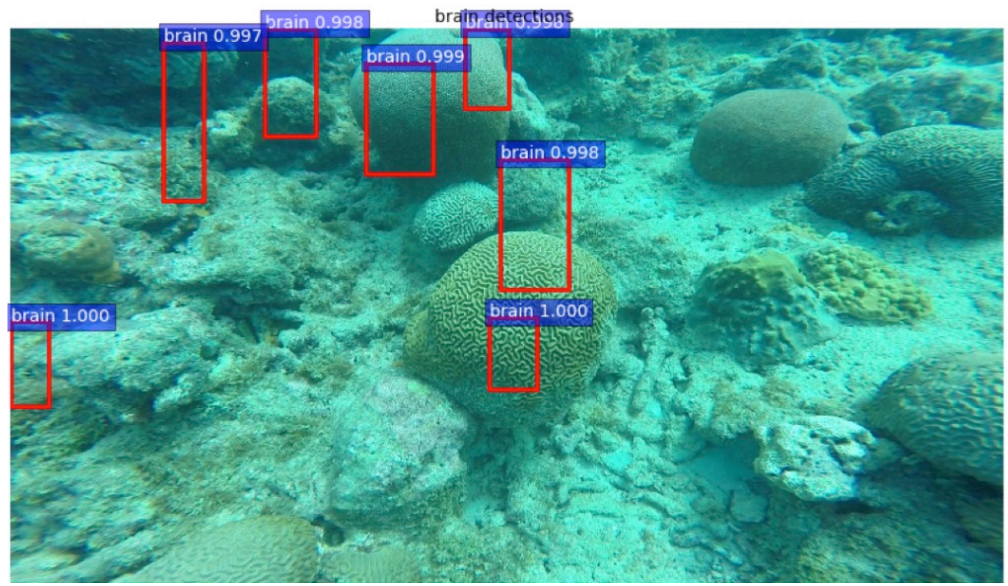
Object recognition

source: http://www.cs.cornell.edu/courses/cs4670/2013fa/

Pedestrian and car detection

Lane detection

From GoPro 3D Hero at Barbados 2015 Field Trial



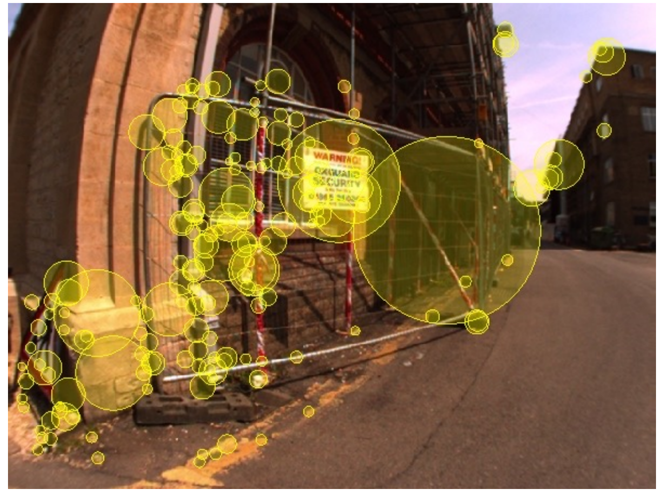
Coral classification

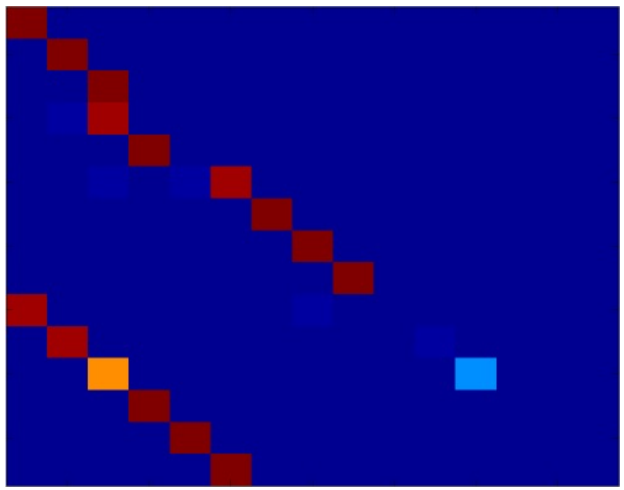
Bag of words

Object → **Bag of ‘words’**

source: http://wikimedia.org

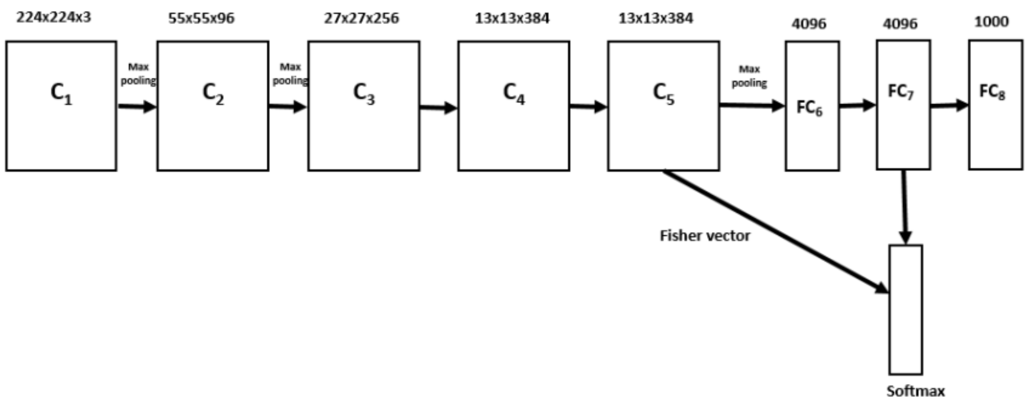
Appearance-based place recognition

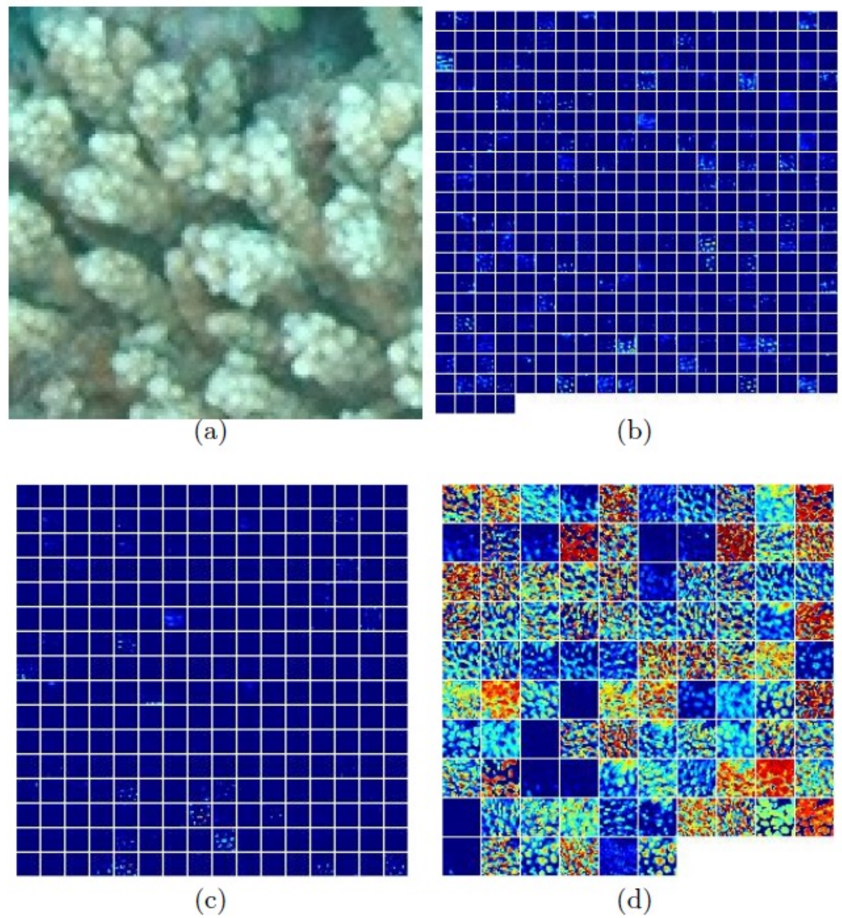




source: http://www.robots.ox.ac.uk/~mjc

Deep learning based classification





Computer Vision Books

- Richard Szeliski, “Computer Vision: Algorithms and Applications”, Springer, 2010
- Richard Hartley and Andrew Zisserman, “Multiple View Geometry in Computer Vision”, Cambridge University Press, 2004
- David Forsyth and Jean Ponce, “Computer Vision: A Modern Approach”, Pearson, 2011

Nice Classes

- Noah Snavely – Introduction to Computer Vision http://www.cs.cornell.edu/courses/cs4670/2013fa/lectures/lectures.html
- Steve Seitz and Rick Szeliski – Computer Vision http://courses.cs.washington.edu/courses/cse576/08sp/