



UNIVERSITY OF
SOUTH CAROLINA

CSCE 590 INTRODUCTION TO IMAGE PROCESSING

Motion and Optical Flow

Correspondence

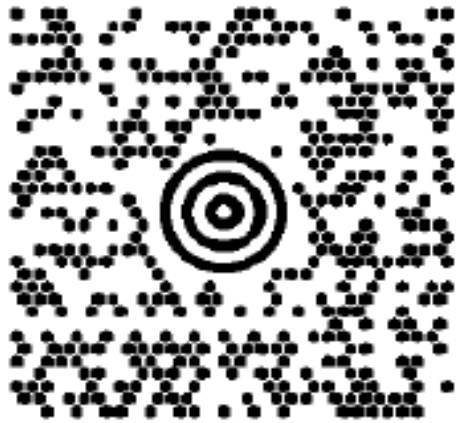
From I_1



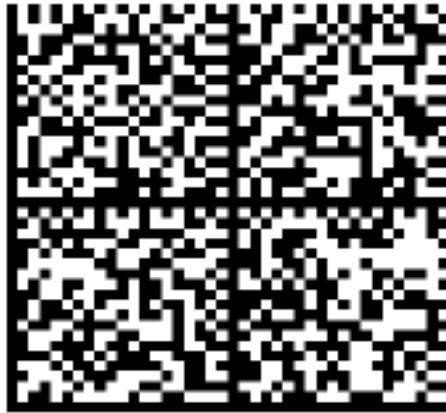
From I_2



Fiduciary Markers/Fiducial



(a) MaxiCode



(b) DataMatrixSymbol



(c) ARToolkit



(d) ARTag



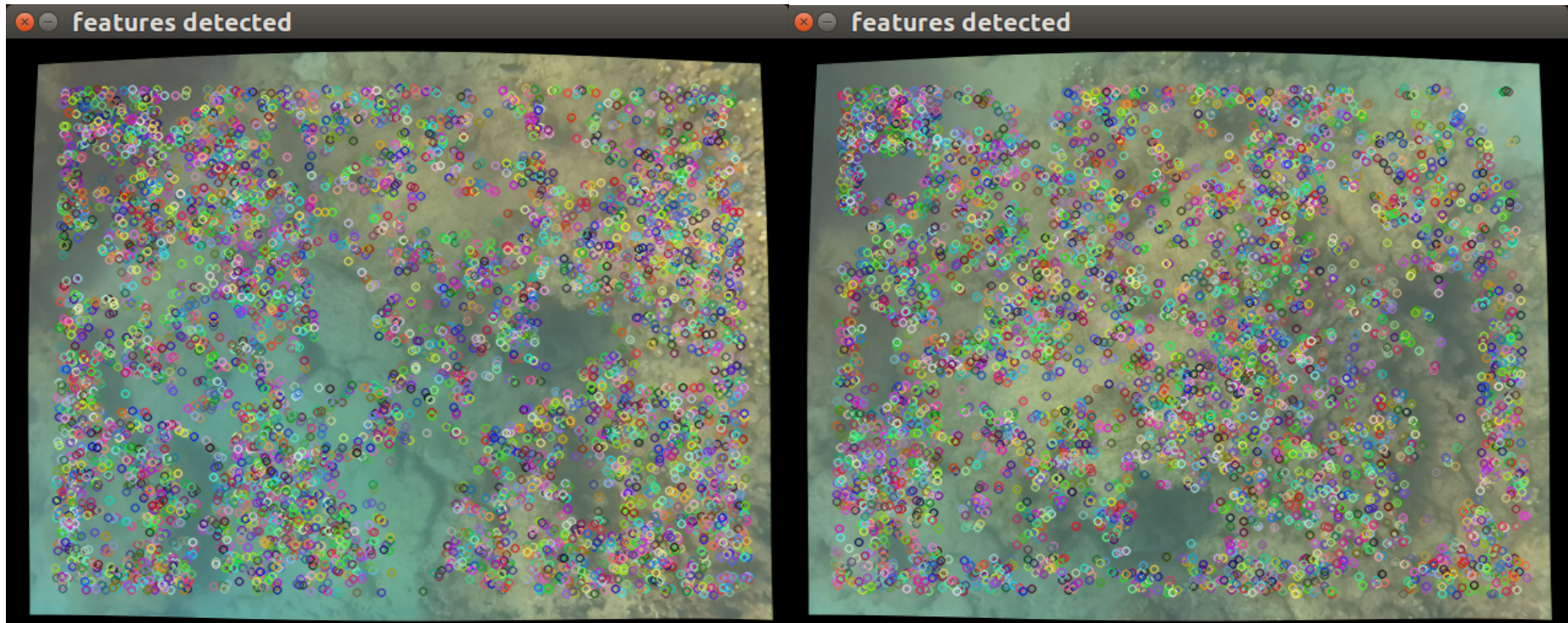
Fourier Tag

Good Feature

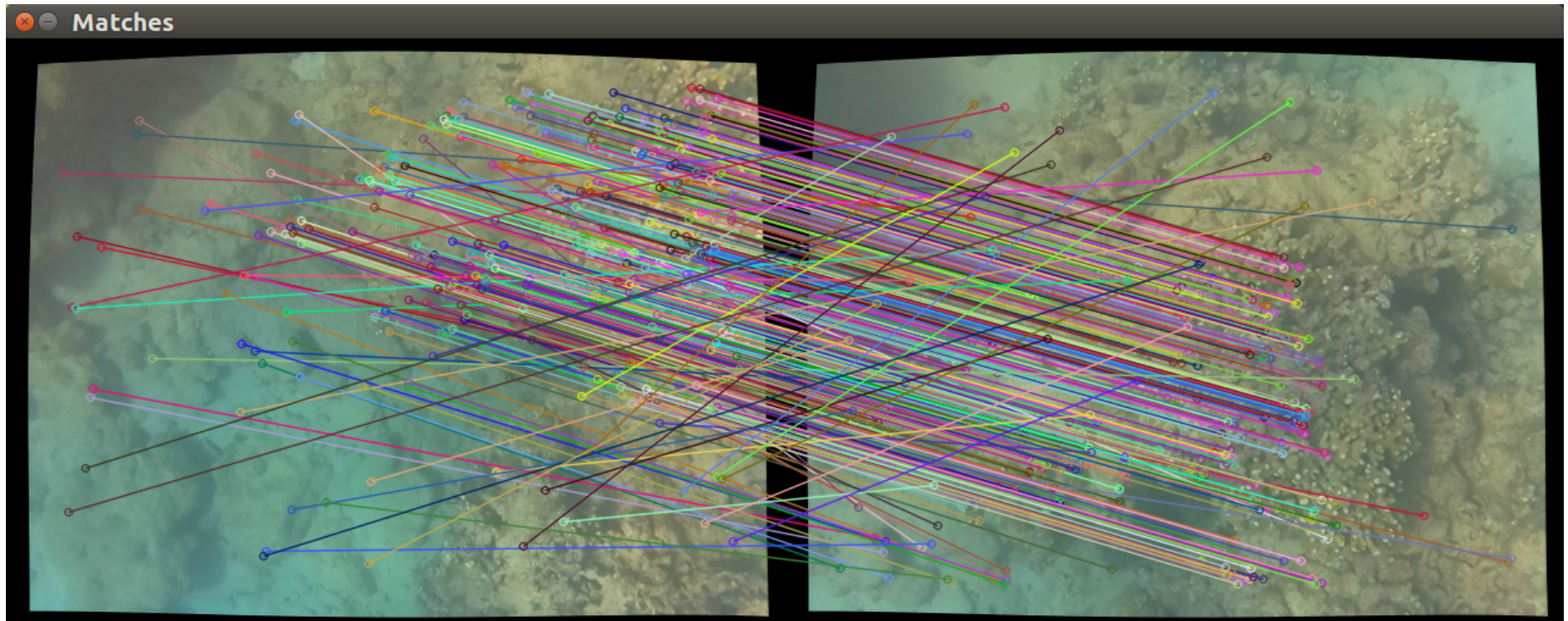
- Invariant to transformations
- Unique
- Efficient to compute
- Good precision and high recall
- Several Alternatives:
 - Harris Corners (OpenCV)
 - SURF (OpenCV)
 - SIFT
 - ORB
 - etc



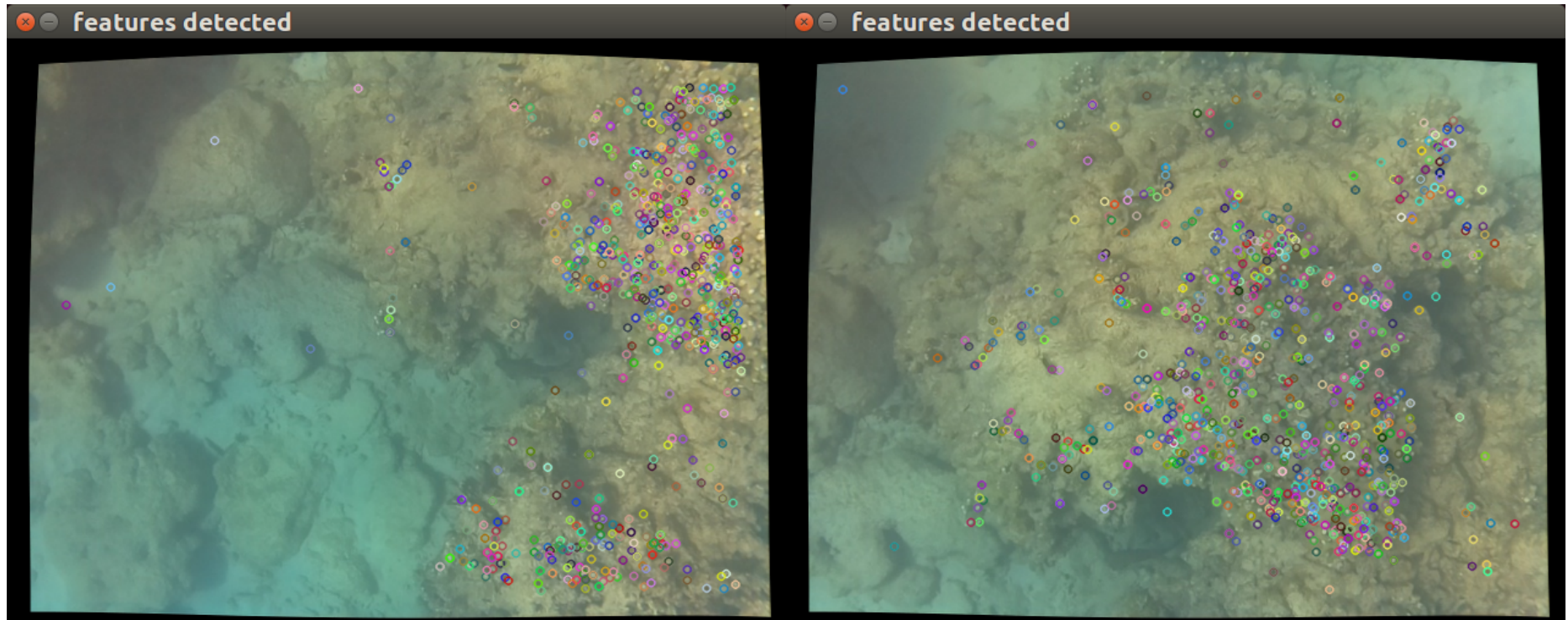
Harris Corners



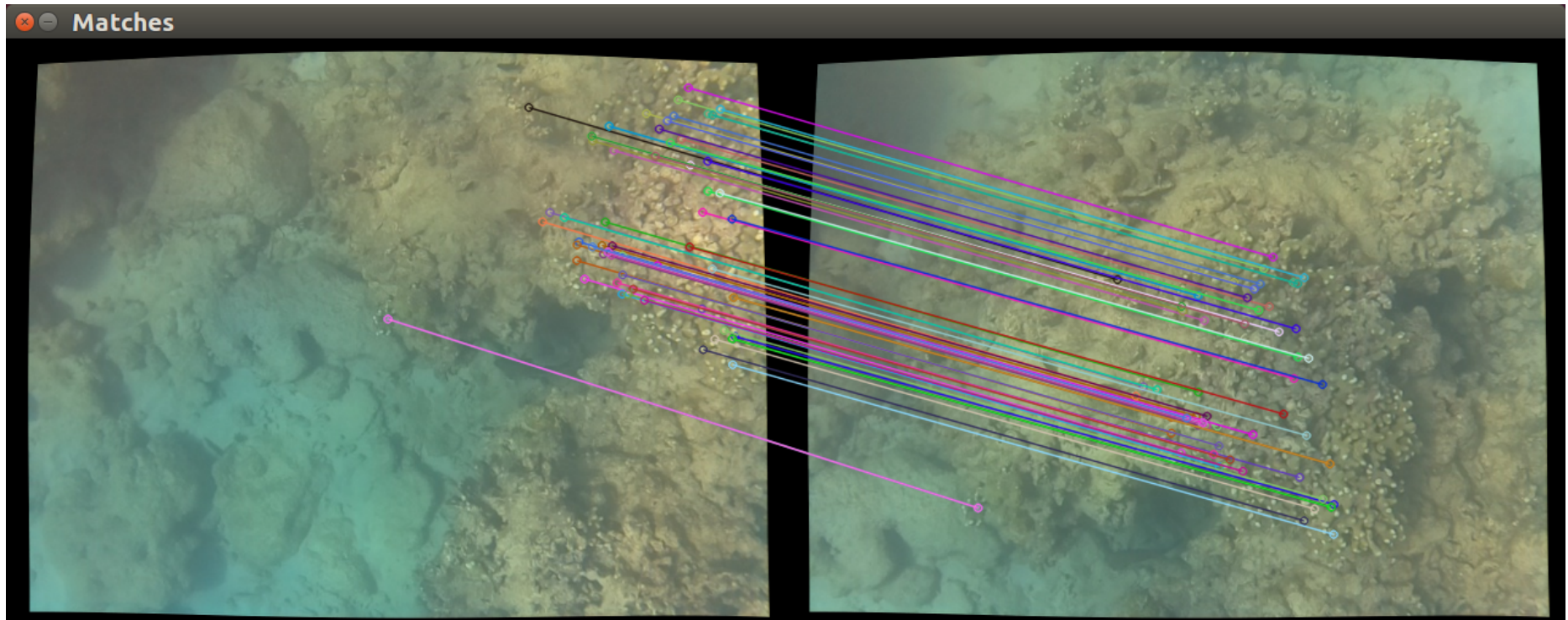
Harris Corners



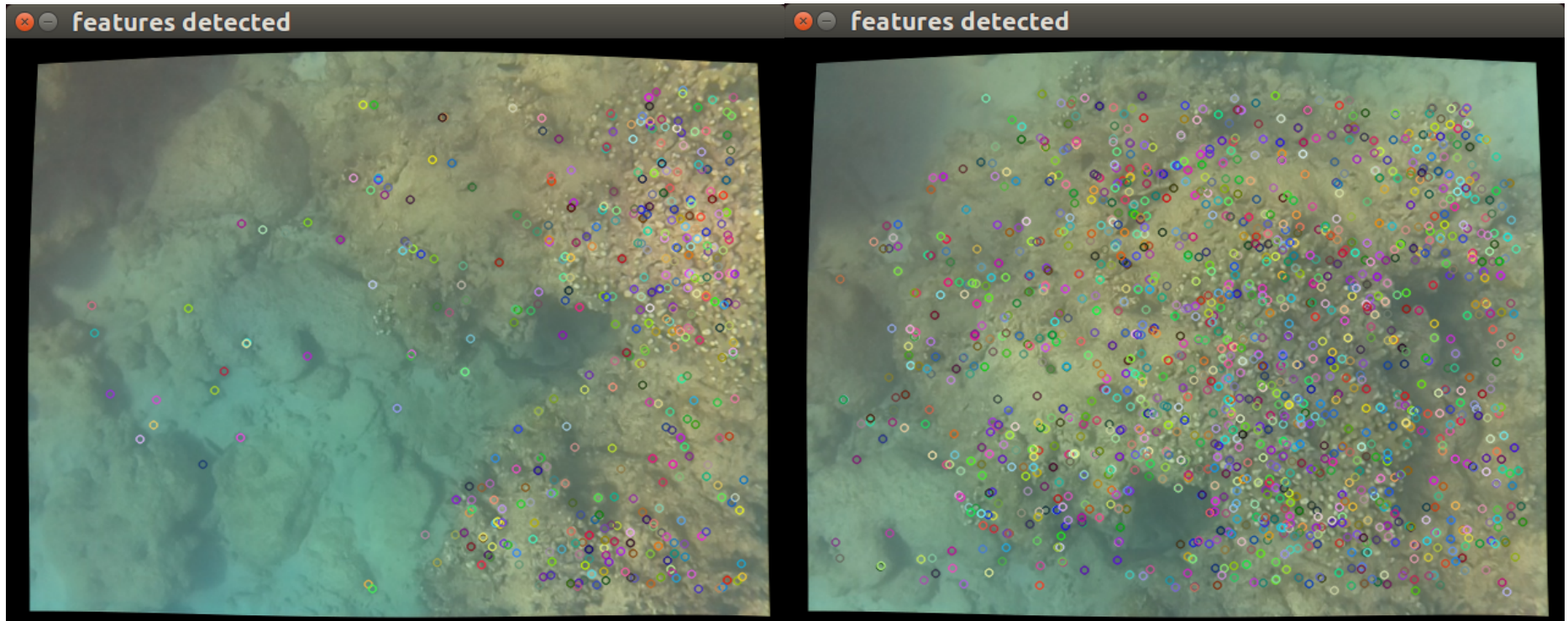
SIFT



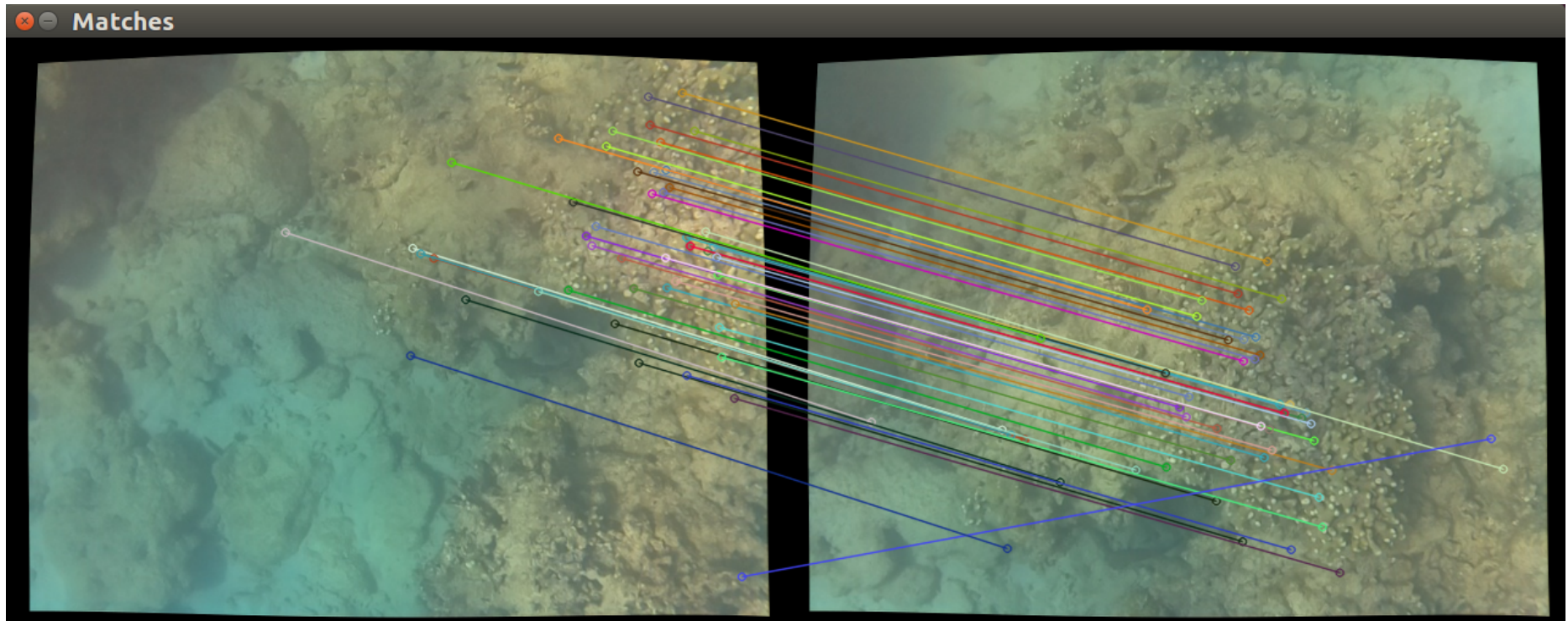
SIFT



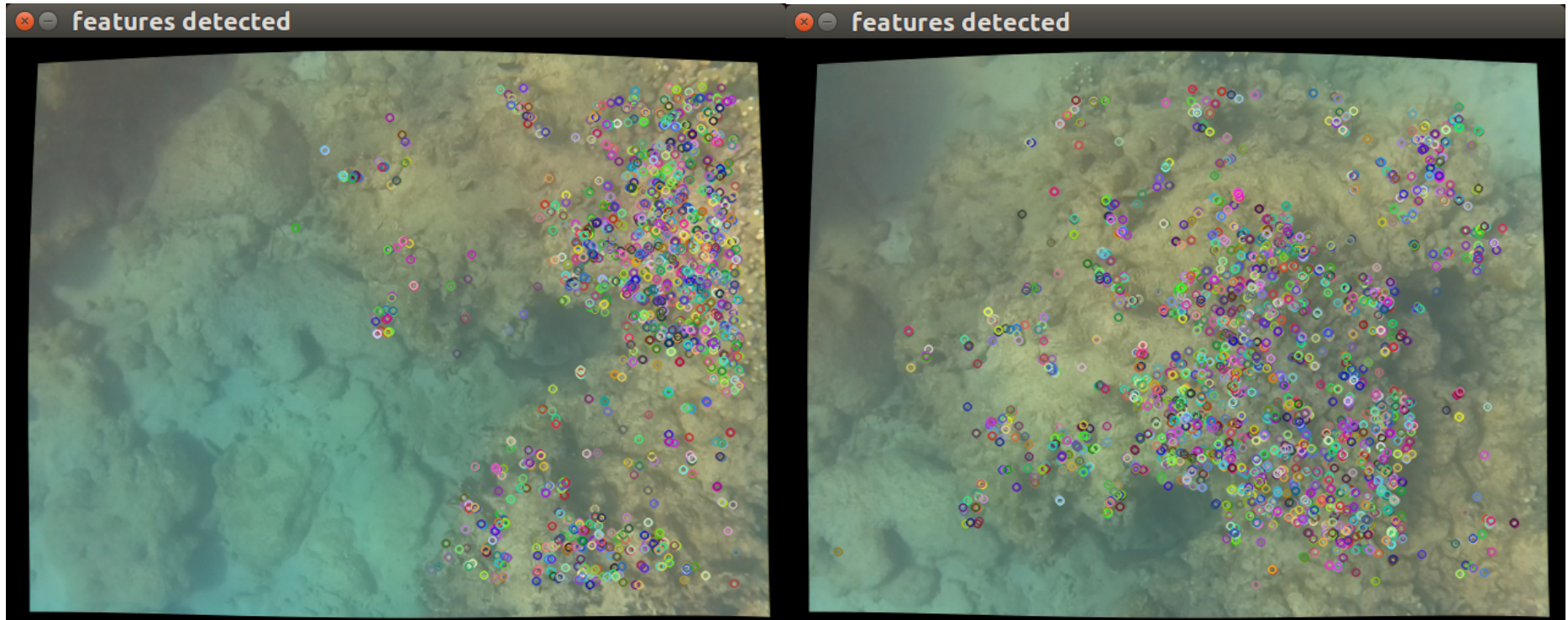
SURF



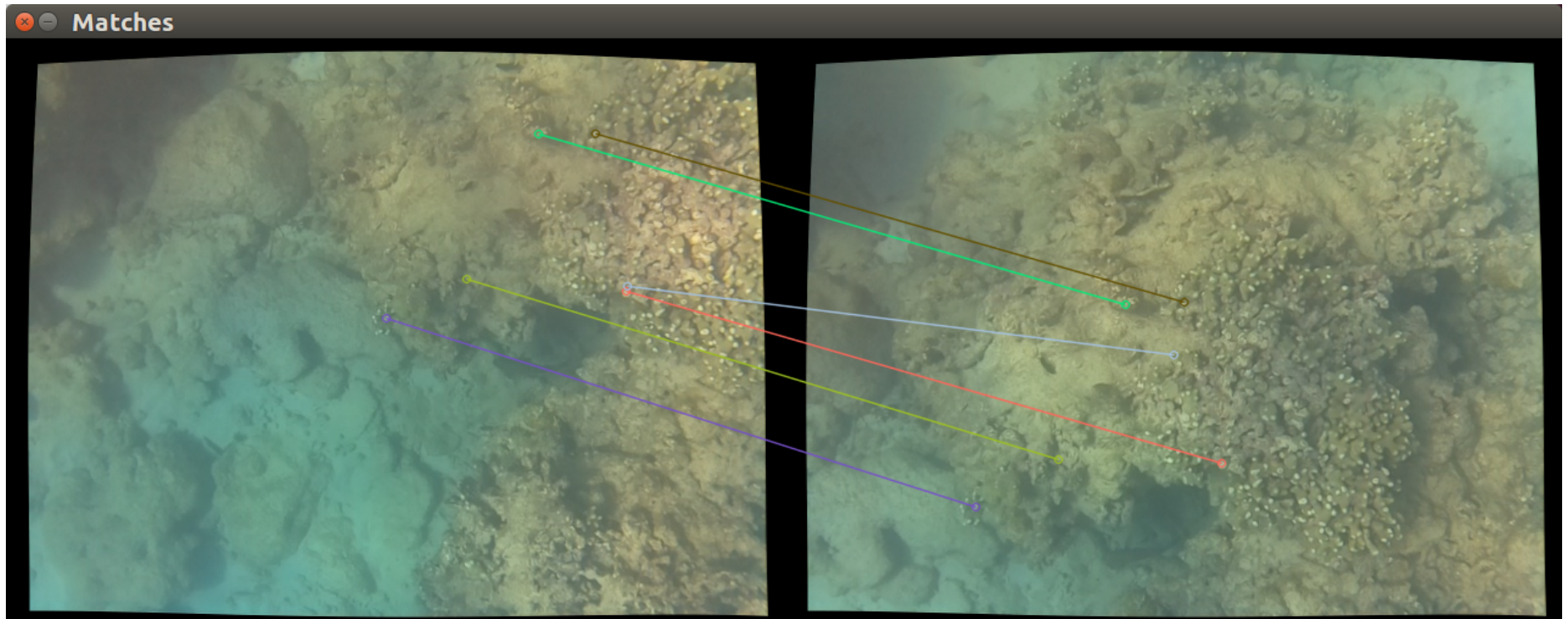
SURF



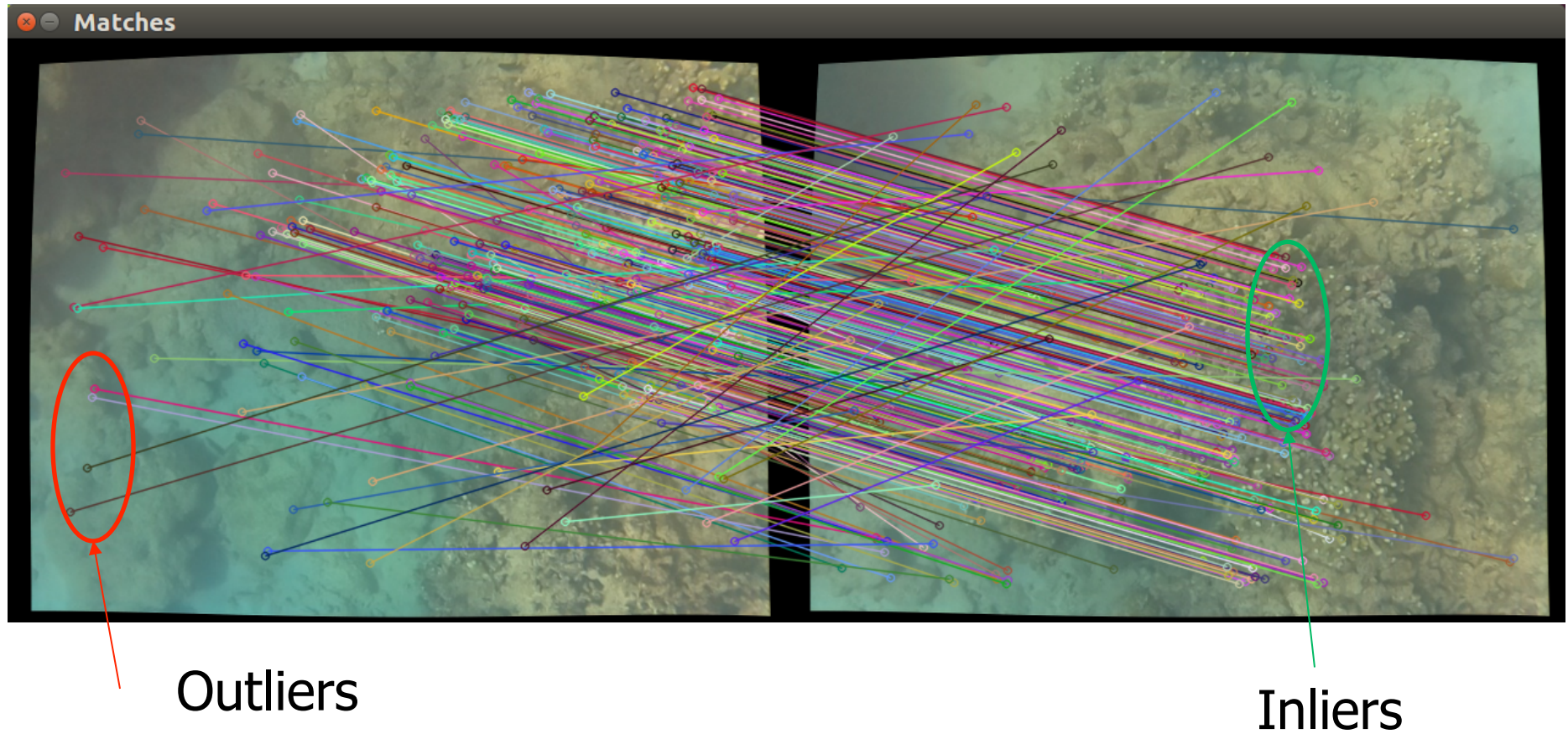
ORB



ORB



Outliers



Outliers

Inliers

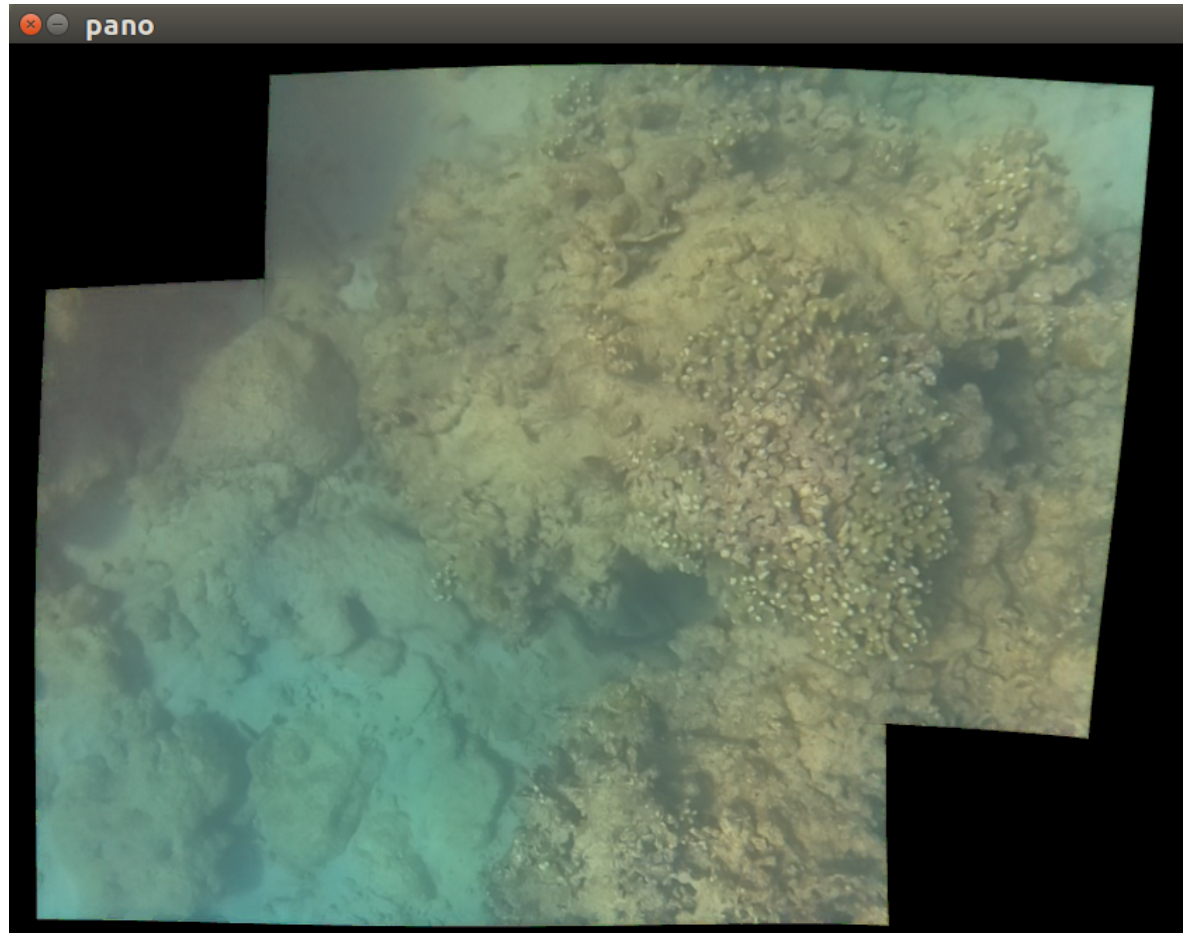


RANSAC

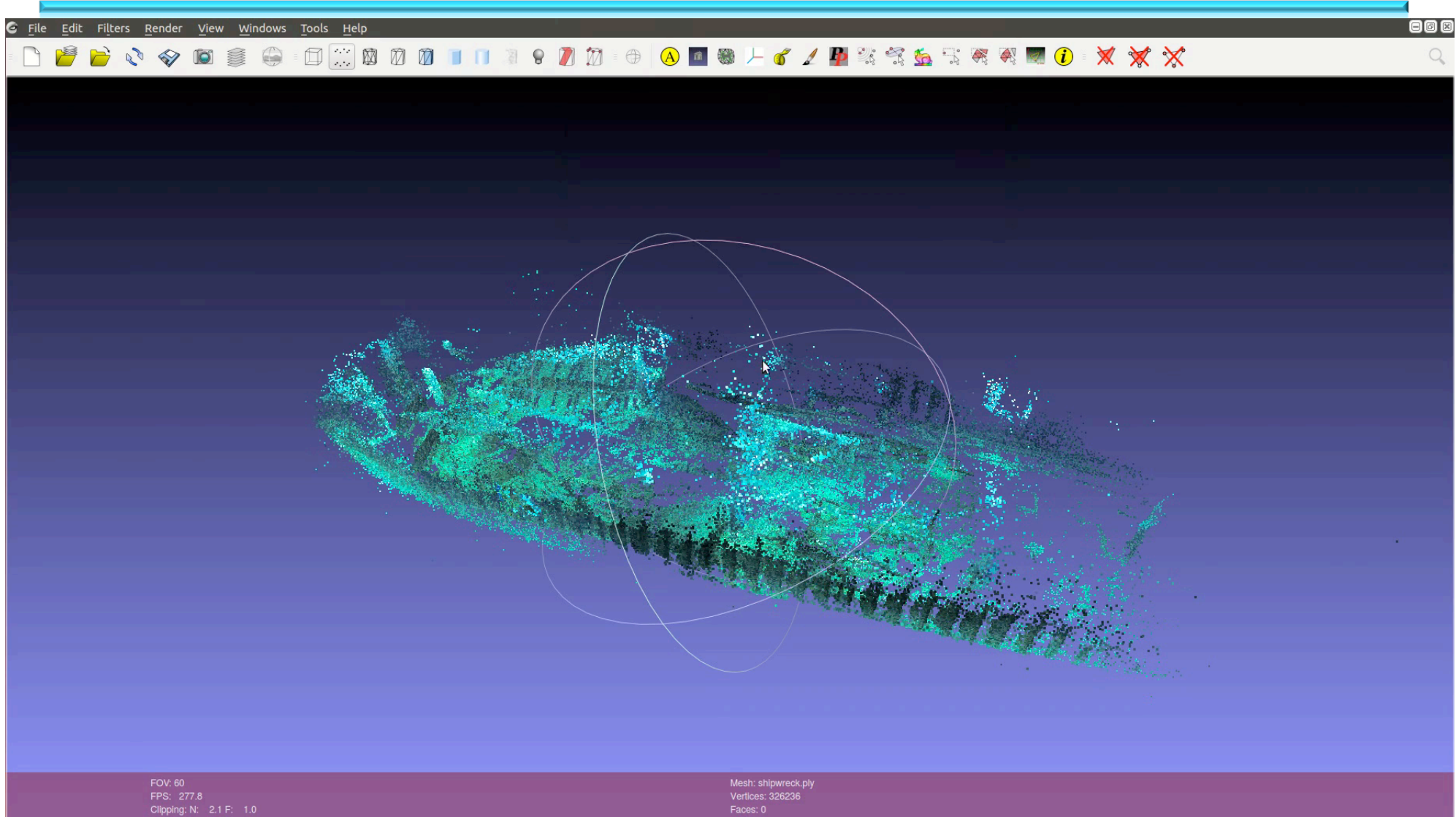
- See Visual Odometry Tutorial Presentation



Mosaic



3D Sparse reconstruction

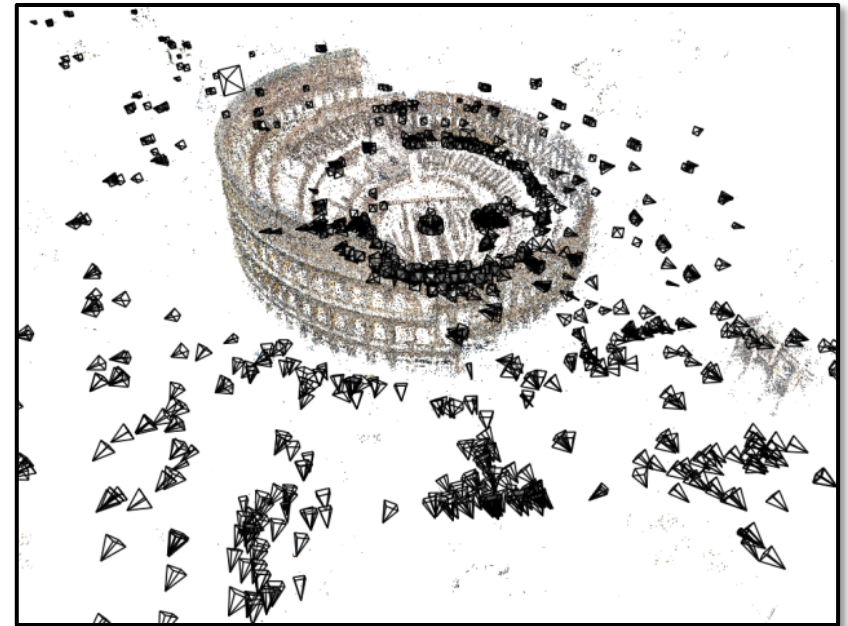
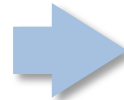


3D Sparse reconstruction

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

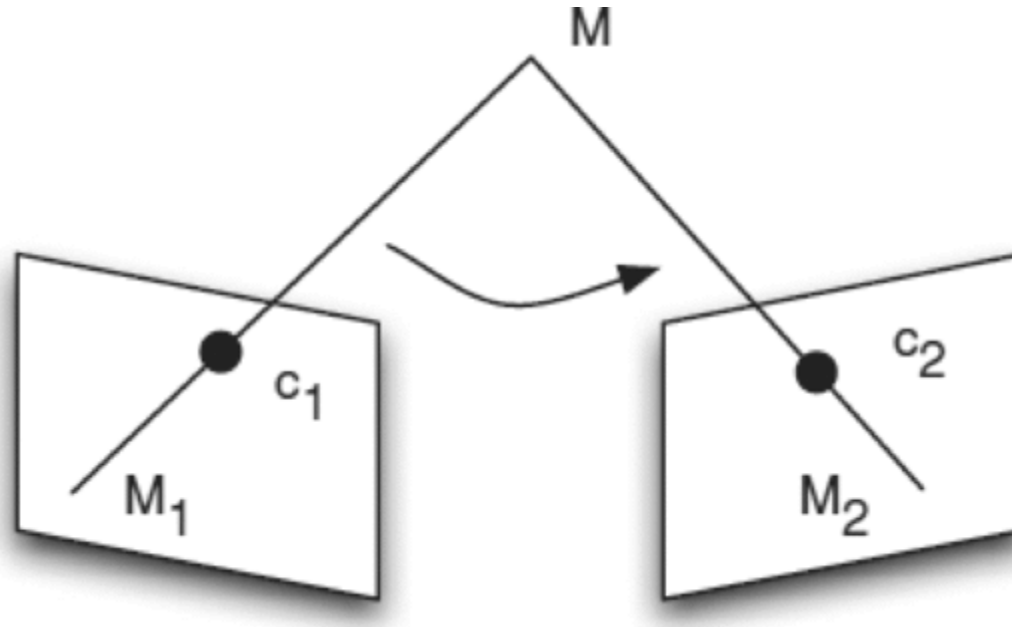


**Internet Photos
("Colosseum")**



**Reconstructed 3D cameras and
points**

Egomotion



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

Visual Odometry/Structure from Motion



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.*

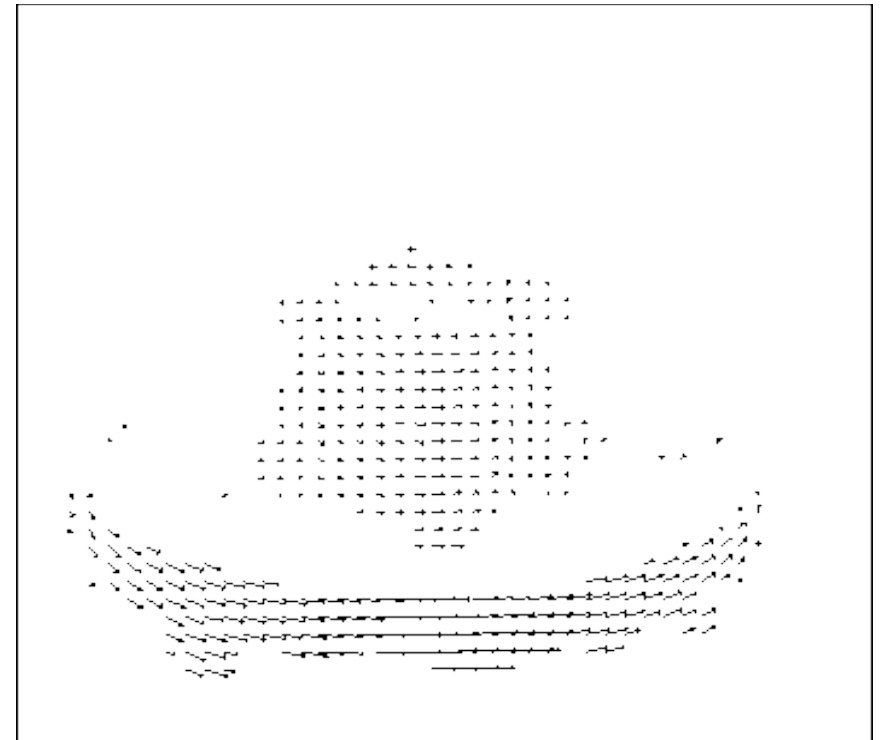


Difference between Optical Flow and Scene Motion

- Optical flow: change in the image (2D)
- Scene Motion: change in the scene (3D)



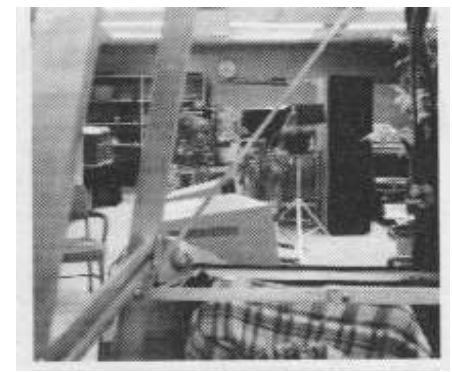
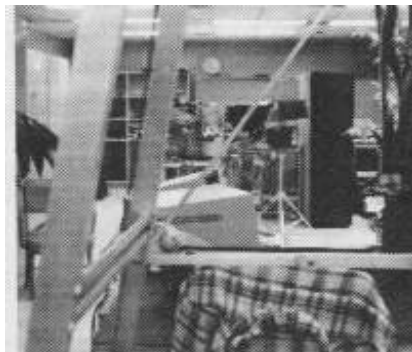
Optical Flow Field



Optical flow

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

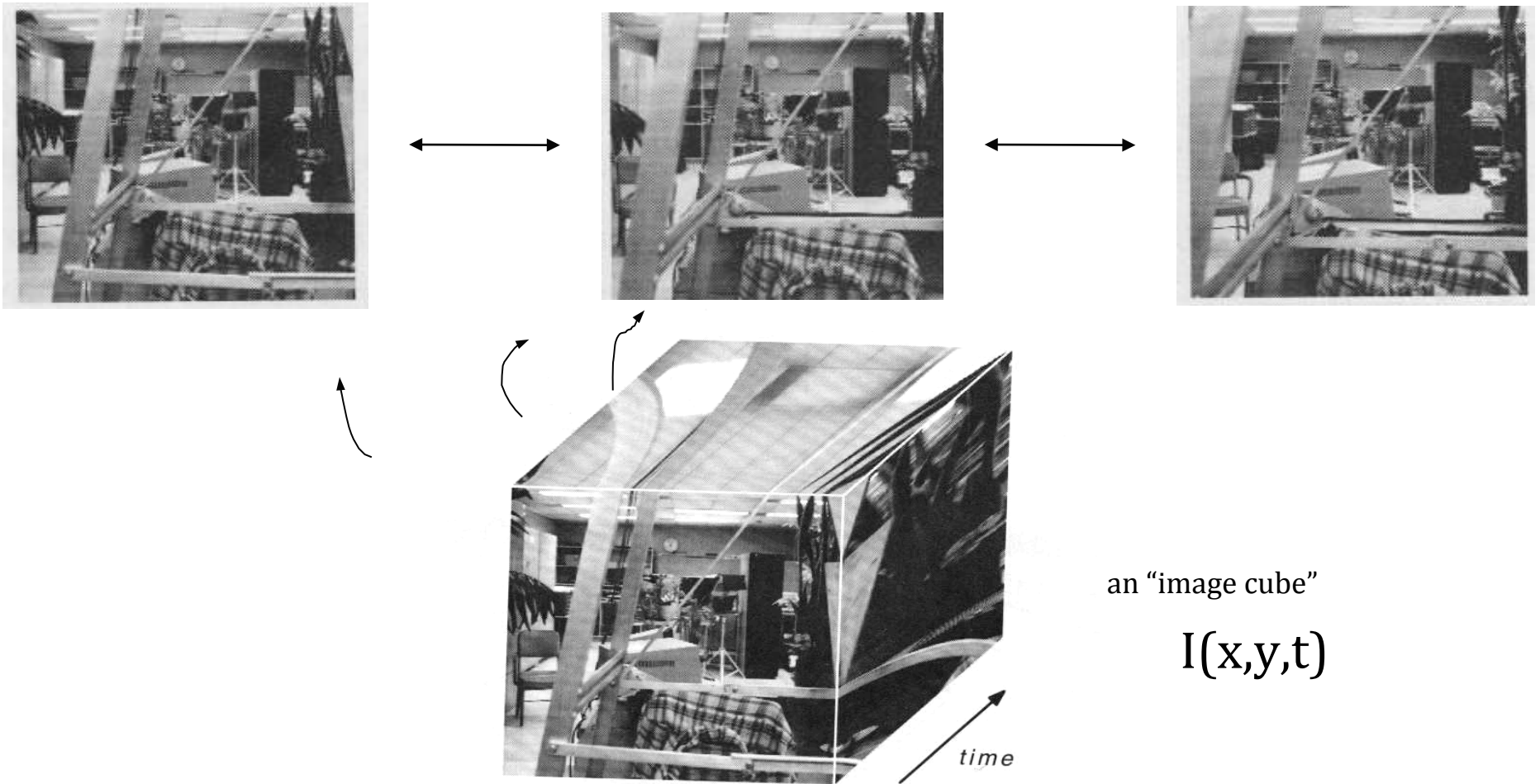
This next step might be to use the image motion to infer scene motion, robot motion or 3D layout.



time sequence of images

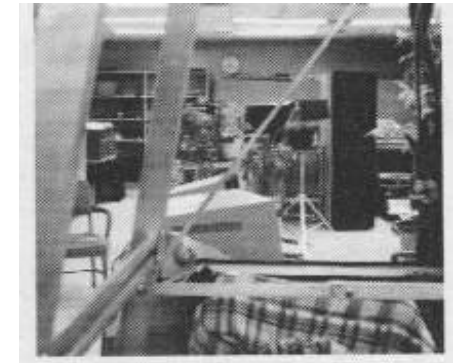
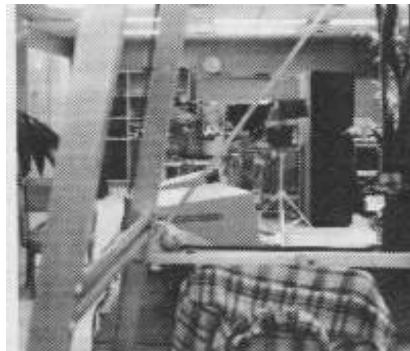
Optical flow

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



Optical flow

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



optical flow

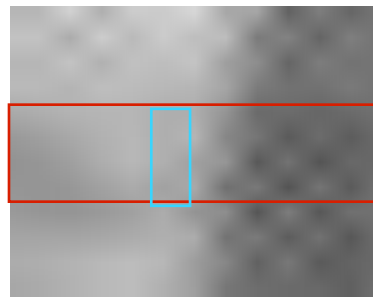
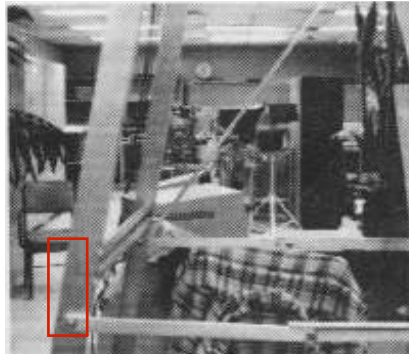
How ?



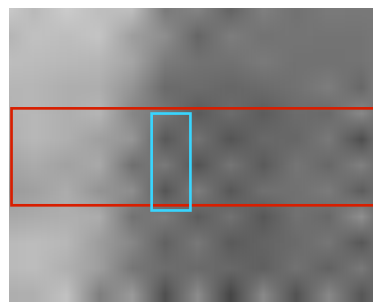
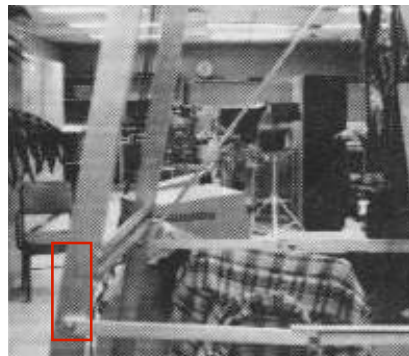
Optical Flow

- 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



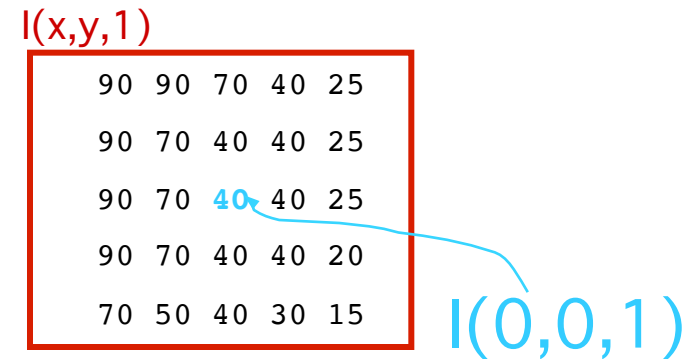
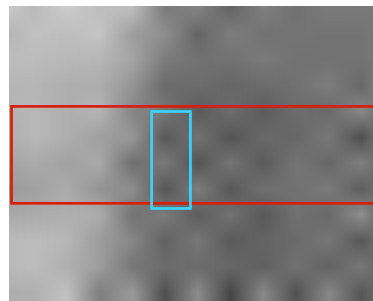
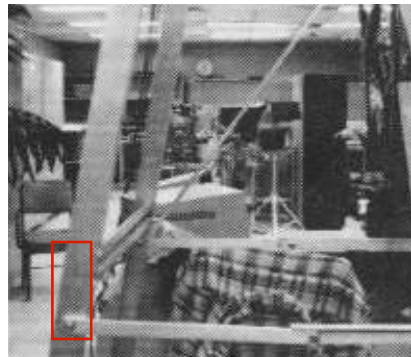
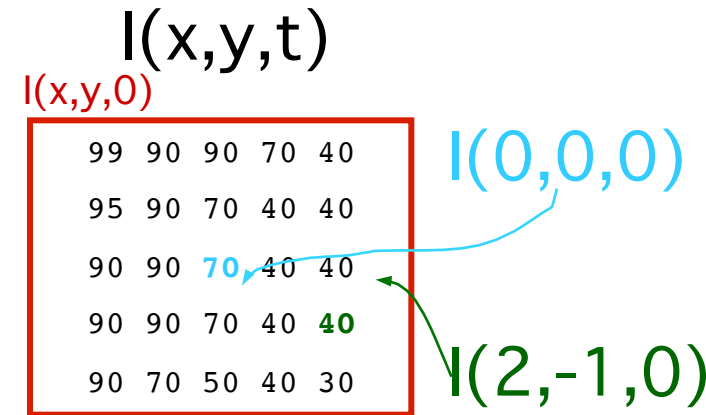
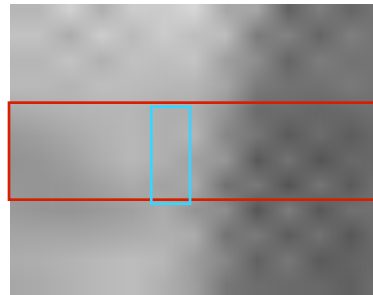
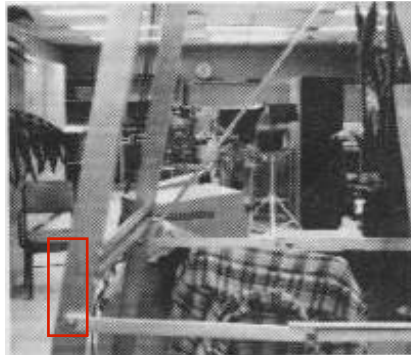
90	90	70	40	25
90	70	40	40	25
90	70	40	40	25
90	70	40	40	20
70	50	40	30	15

- We can estimate things...



Optical Flow

By measuring the direction that intensities are moving...



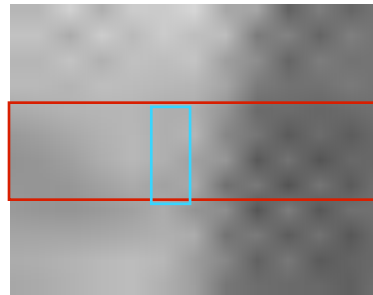
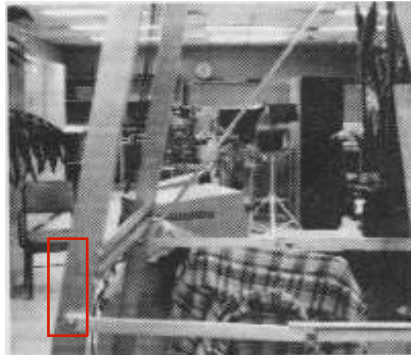
We can estimate things ...

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



Optical Flow

By measuring the direction that intensities are moving...



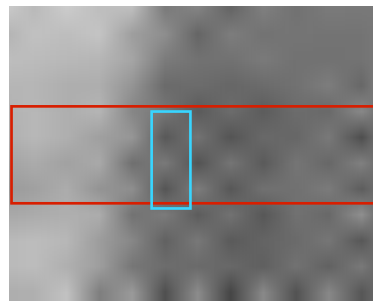
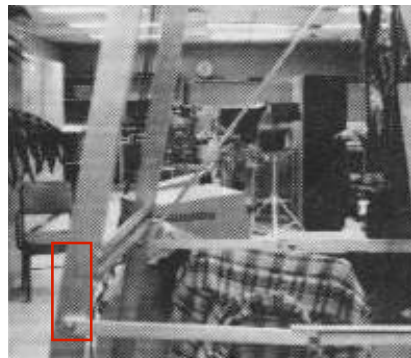
$I(x,y,t)$

$I(x,y,0)$

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

$I(0,0,1)$

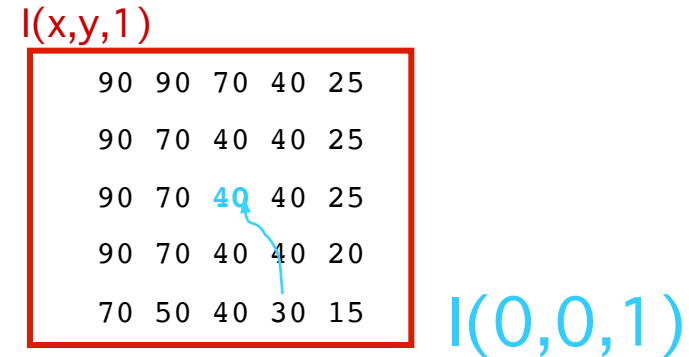
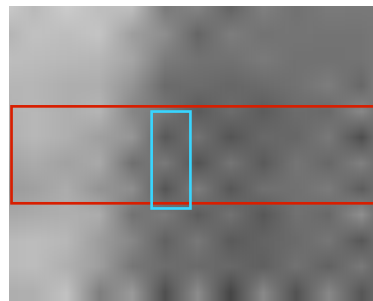
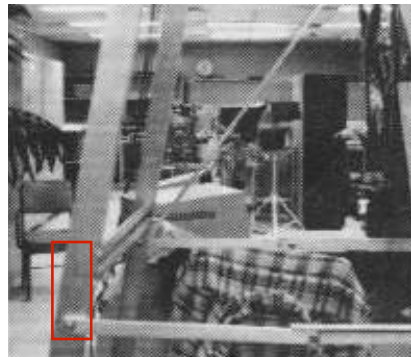
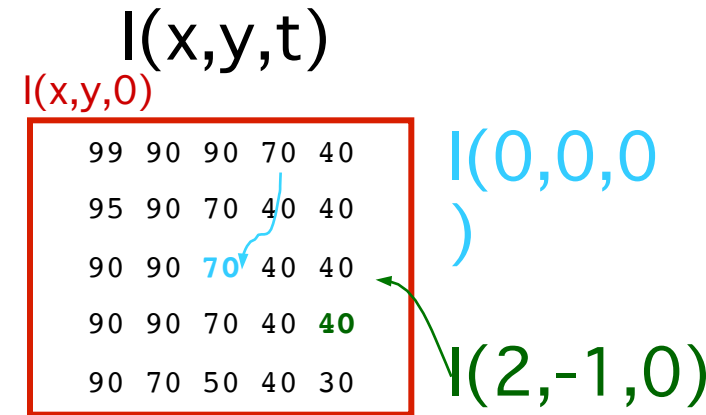
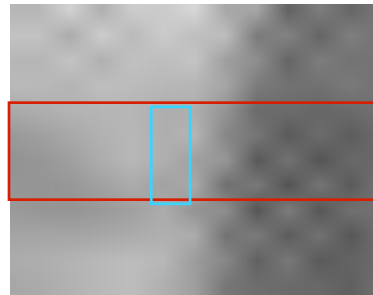
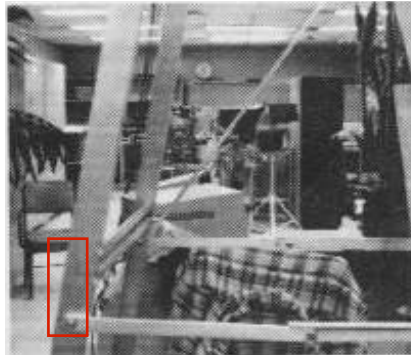
We can estimate things like

$$\frac{dI}{dx} = I_x \text{ at } (0,0,0) = \frac{\Delta I}{\Delta x} = \frac{I(1,0,0) - I(0,0,0)}{1 - 0} = -30$$



Optical Flow

By measuring the direction that intensities are moving...



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)



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95	90	70	40	40
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Reminder: $f(x + dx) = f(x) + f'(x) dx + f''(x) dx^2 / 2 + \dots$



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



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

ignore these terms



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

ignore these terms

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

intensity-flow equation

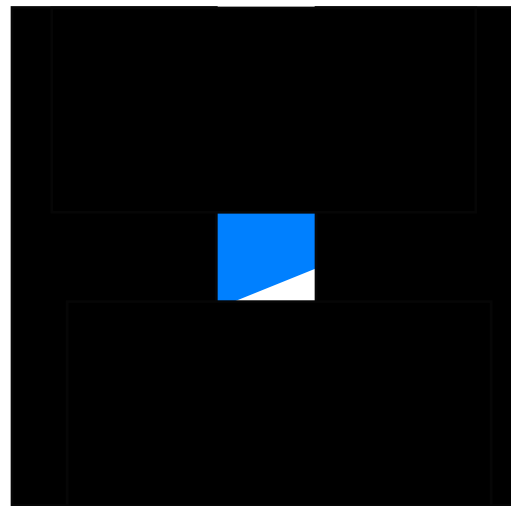
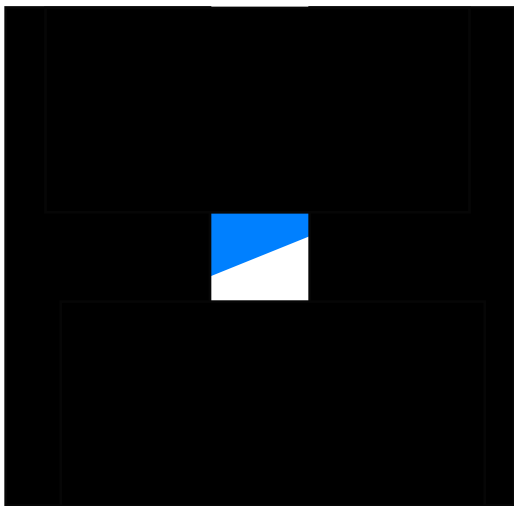
good and bad...



The “aperture” problem

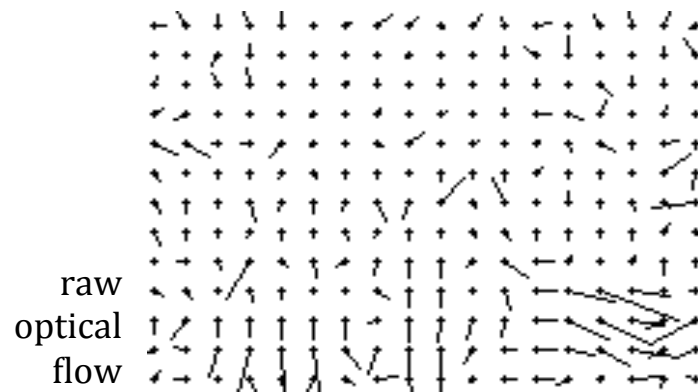
$$-I_t = I_x \frac{dx}{dt} + I_y \frac{dy}{dt}$$

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



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.



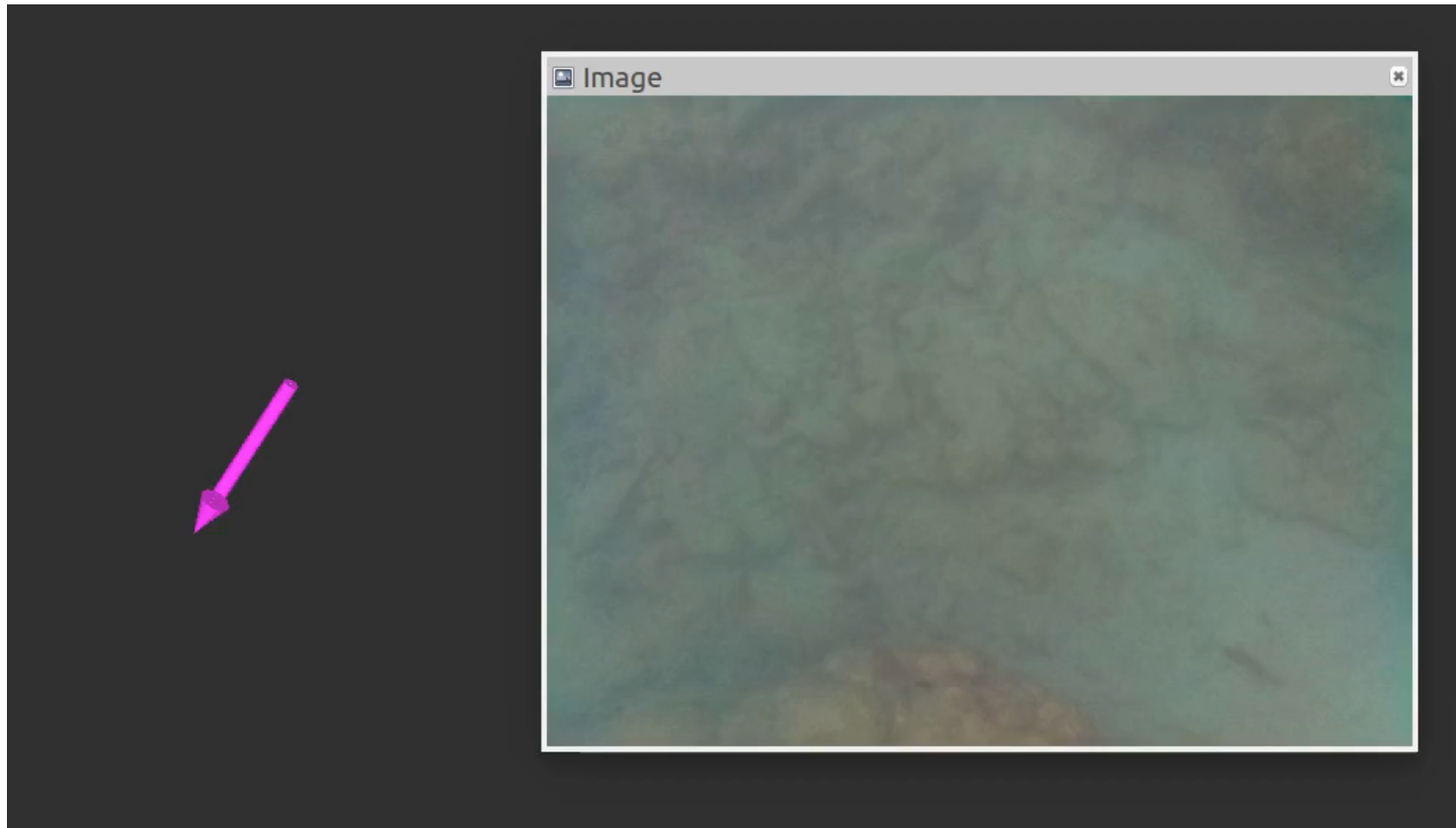
Features vs Optical Flow

- 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

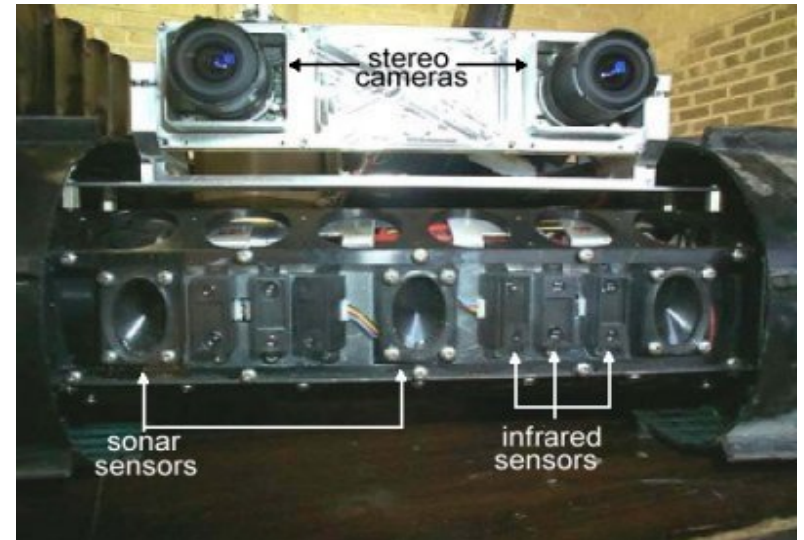


A Vision “solution”

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



multiple cameras



multiple times



Object recognition

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

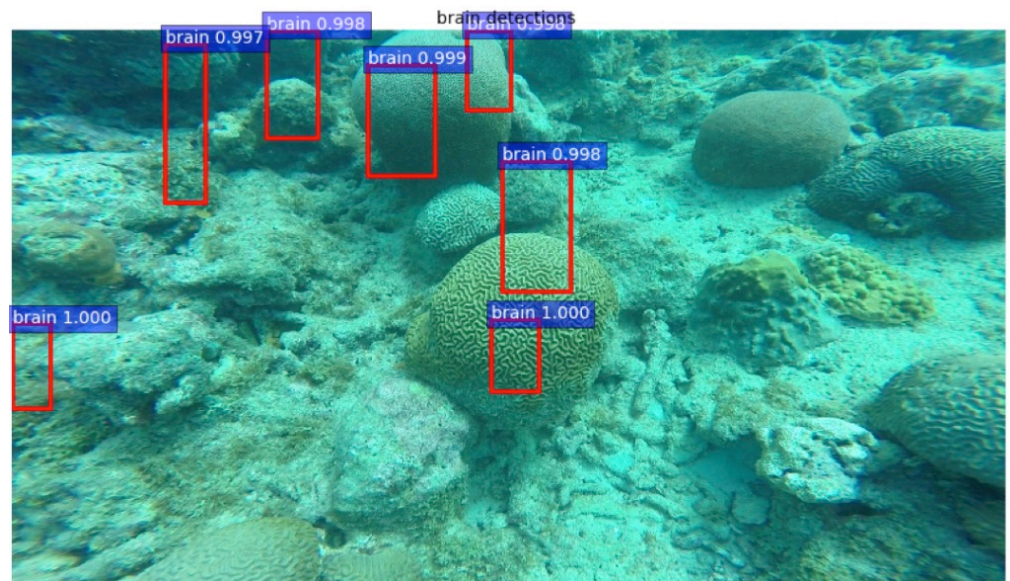


Pedestrian and car detection



Lane detection

From GoPro 3D Hero at Barbados 2015 Field Trial



Coral classification



Bag of words

Object



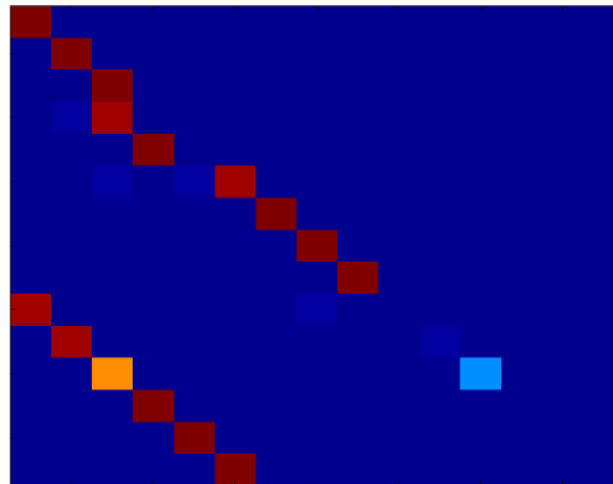
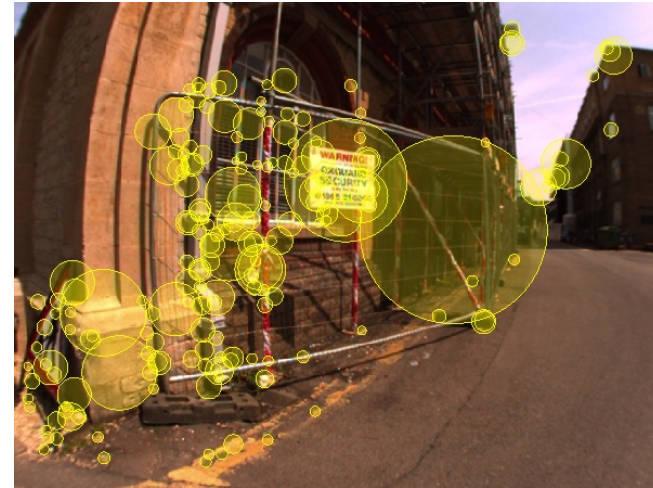
Bag of 'words'



source: <http://wikimedia.org>



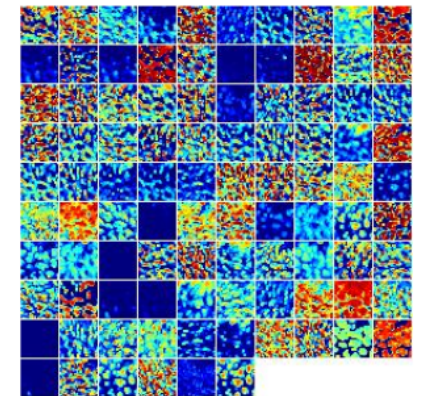
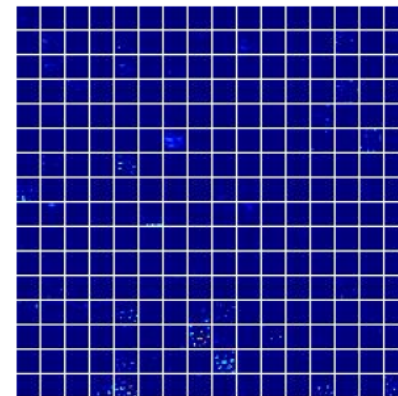
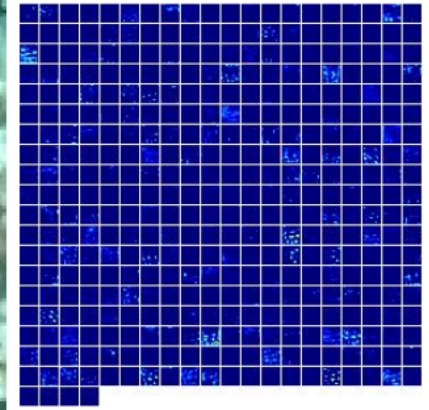
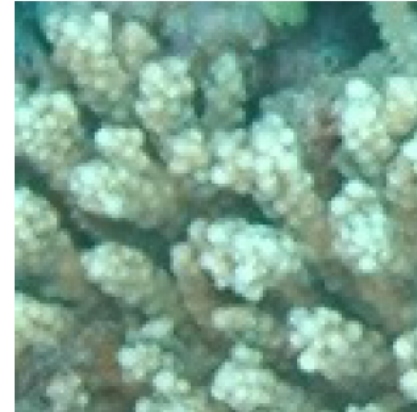
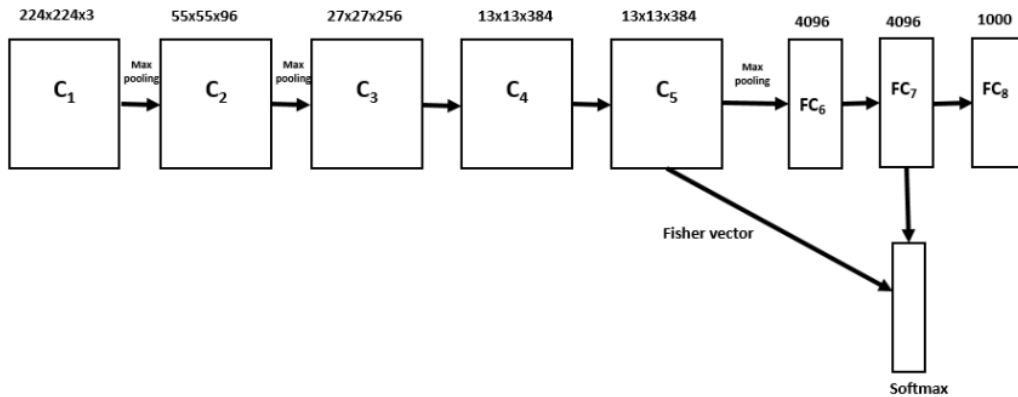
Appearance-based place recognition



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/>



Questions?

