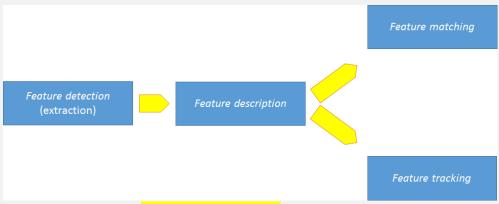


Chapter 3

- 1. Feature detection and matching are an essential component of many computer vision applications:
 - a. Automate object tracking
 - b. Point matching for computing disparity
 - c. Stereo calibration and Estimation of fundamental matrix
 - d. Motion based segmentation
 - e. Recognition
 - f. 3D object reconstruction
 - g. Robot navigation
 - h. Image retrieval and indexing
 - i. All of the above
- 2. 1st approach: Find features in one image that can be accurately tracked using a search technique.
 - a. Local
 - b. Global
- 3. 1st approach: Example of local search techniques:
 - a. Correlation
 - b. Least squares
 - c. All of the above
- 4. 1st approach: We use local search techniques when images are taken from nearby viewpoints or in rapid succession (e.g., video sequences).

	a.	<u>True</u>
	b.	False
5.	2 nd ap	pproach: Independently <mark>detect features in all the images</mark> under
	consi	deration and then match features based on their
	appea	arance.
	a.	<u>Local</u>
	b.	Global
6.	2 nd ap	pproach: A amount of motion or appearance change is
	exped	cted.
	a.	Little
	b.	<u>Large</u>
7.	2 nd ap	pproach: Stitching together <mark>panoramas</mark> .
	a.	<u>True</u>
	b.	false
8.	2 nd ap	pproach: in wide baseline stereo.
	a.	Establishing correspondences
	b.	Establishing features
	c.	Establishing edges
9.	2 nd ap	pproach: Performing
	a.	Object recognition
	b.	Histogram equalization
10	.Steps	of Keypoint detection:
	a.	Feature detection(extraction)
	b.	Feature description, then
		i. Feature matching(images)

ii. Feature tracking(videos)



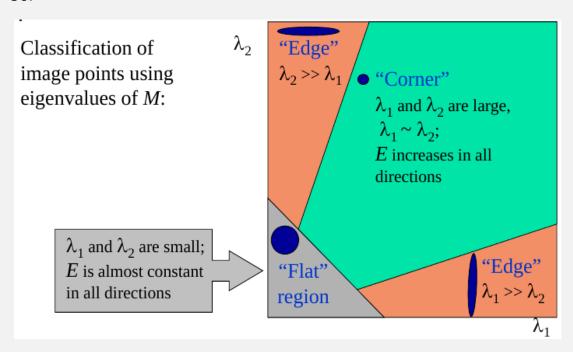
- 11. Interest point has expressive texture.
 - a. True
 - b. false
- 12.Interest point is the point at which the direction of the boundary of object changes
 - a. Gradually
 - b. Abruptly (suddenly)
 - c. Smoothly
- 13.Interest point is the Intersection point between two or more edge segments.
 - a. True
 - b. False
- 14. Properties of Interest Point Detectors:
 - a. Detect all (or most) true interest points.
 - b. No false interest points.
 - c. Well localized.
 - d. Robust with respect to noise.
 - e. Efficient detection.

15.Interest	t point detectors permit matching even in the presence of		
<mark>clutter</mark>	(occlusion), large scale, illumination change and orientation		
<mark>change</mark> :	<mark>s</mark> .		
a. <u>T</u>	<u>rue</u>		
b. f	alse		
16 Identify the interest points .			
a. <u>d</u>	<u>letection</u>		
b. d	description		
c. n	natching		
17	, Extract feature vector descriptor surrounding each		
interest	t point.		
a. D	Detection		
b. <u>C</u>	<u>Description</u>		
c. N	Matching		
18	, Determine <mark>correspondences</mark> between <mark>two descriptors</mark> in		
two views.			
a. D	Detection		
b. D	Description		
c. <u>N</u>	Matching		
19.Feature	e descriptor must provide some invariance to geometric and		
<mark>photon</mark>	netric differences between the two views.		
a. <u>T</u>	<u>rue</u>		
b. F	alse		
20. Texture	e-less patches are nearly to localize.		
a. P	Possible		

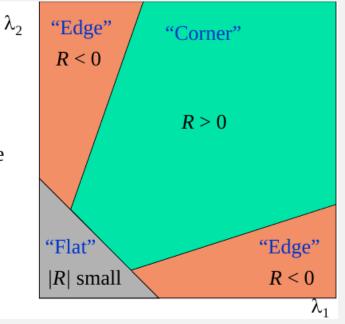
b.	<u>Impossible</u>	
21.Patch	es with large changes (gradients) are <mark>easier to localize</mark>	
a.	Brightness	
b.	Saturation	
c.	Contrast	
22. <mark>Straig</mark>	ht line segments at a single orientation suffer from the	
a.	Shutter speed	
b.	Aperture problem	
c.	Iso	
23.No ur	nique match	
a.	Aperture problem	
b.	Shutter speed problem	
c.	Iso problem	
24	, Frequency with which key-point detected in one image	
are fo	ound within E (say, <mark>E=1.5</mark>) pixels of the corresponding location	
in a transformed image.		
a.	Measuring repeatability	
b.	Scale invariance	
C.	Rotational variance and orientation estimation	
d.	Affine invariance	
25. ε=		
a.	1	
b.	1.25	
c.	<u>1.5</u>	

- d. 2
- 26.Performing the same operations at multiple resolutions in a pyramid and then matching features at the same level.
 - a. Measuring repeatability
 - **b.** Scale invariance
 - c. Rotational variance and orientation estimation
 - d. Affine invariance
- 27. They also respond consistently across affine deformations such as (local) perspective foreshortening.
 - a. Measuring repeatability
 - b. Scale invariance
 - c. Rotational variance and orientation estimation
 - d. Affine invariance
- 28. The Simplest Possible Matching Criterion
 - a. Weighted summed square difference
 - b. auto-correlation function or surface
 - c. all of the above
- 29. Comparing an image patch against itself (respect to small variations), which is known as
 - a. Weighted summed square difference
 - b. <u>auto-correlation function or surface</u>
- 30. Approaches to corner detection
 - a. Based on brightness of images
 - i. Usually image derivatives
 - b. Based on boundary extraction

i. First step <mark>edge</mark> detection
ii. Curvature analysis of <mark>edges</mark>
31. Shifting a window in any direction should give a large change in
intensity.
32. Significant change in all directions.
a. Flat
b. Edge
c. <u>Corner</u>
33. No change in all directions
a. <u>Flat</u>
b. Edge
c. Corner
34.No change along edge direction
a. Flat
b. <u>Edge</u>
c. Corner
35 are good because they don't have aperture problem
a. Flat
b. Edge
c. <u>Corner</u>



- *R* depends only on eigenvalues of M
- *R* is large for a corner
- *R* is negative with large magnitude for an edge
- |R| is small for a flat region



37.

38. Multiply & maximize

a. Correlation

- b. Sum square difference(SSD)
- c. Taylor's series

39. <mark>Subtract</mark> & minimize
a. Correlation
b. <u>Sum square difference(SSD)</u>
c. Taylor's series
40. Can be represented at a point in terms of it's derivatives
a. Correlation
b. Sum square difference(SSD)
c. <u>Taylor's series</u>
41.If pixel value is greater than its neighbors, then it is a
a. local minima
b. <u>local maxima</u>
c. global maxima
d. global minima
42. The local motion around each feature point may be mostly
translational translational
a. <u>true</u>
b. false
43. The local appearance of features will change, if there is a change in
orientation, scale, and undergo affine deformations
a. <u>True</u>
b. False
44.MOPS stands for

a. Multi-frame Organic potatoes

b. Multi-scale Oriented Patches

45.To compensate for slight inaccuracies in the feature point detector		
(location, orientation, and scale), are sampled at a spacing of		
pixels relative to the detection scale		
a. MOPS, four		
b. MOPS, five		
c. MOPS, six		
d. MOPS, ten		
46. Using a level of the image pyramid to avoid aliasing		
a. <u>Coarser</u>		
b. High		
c. Low		
d. Mid		
47.To compensate for affine photometric variations, patch intensities		
are so that their <mark>mean</mark> is and <mark>variance</mark> is		
are so that their mean is and variance is a. re-scaled, one, one		
a. re-scaled, one, one		
a. re-scaled, one, oneb. re-scaled, zero, two		
a. re-scaled, one, oneb. re-scaled, zero, twoc. re-scaled, zero, one		
 a. re-scaled, one, one b. re-scaled, zero, two c. re-scaled, zero, one d. re-scaled, five, one 		
 a. re-scaled, one, one b. re-scaled, zero, two c. re-scaled, zero, one d. re-scaled, five, one 48.the resulting non-negative values form a row version of the SIFT 		
 a. re-scaled, one, one b. re-scaled, zero, two c. re-scaled, zero, one d. re-scaled, five, one 48. the resulting non-negative values form a row version of the SIFT descriptor vector		
 a. re-scaled, one, one b. re-scaled, zero, two c. re-scaled, zero, one d. re-scaled, five, one 48.the resulting non-negative values form a row version of the SIFT descriptor vector a. 126 		

49...... computes the x and y derivatives over a 39x39 patch and then reduces the resulting 3042-dimensional vector to 36 a. SIFT Detector b. PCA-SIFT Detector 50. SURF uses to approximate the derivatives and integrals used in SIFT a. Average filter b. box filters c. median filter d. linear filter 51. Gradient Location-orientation Histogram (GLOH) Detector is invariant on SIFT that uses a log-polar binning structure instead of the four quadrants a. True b. False (variant) 52. The spatial bins are of radius 6, 11, and 15, with eight angular bins (except for the central region), for a total of 17 spatial bins and 16 orientation bins a. True b. False 53. The 272-dimensional histogram is then projected onto a dimensional descriptor using PCA trained on a large database a. 123 b. 200 c. 128

- d. 256
- 54. GLOH has the over all better performance and it outperforms by a SIFT small margin
 - a. True
 - b. False
- 55. Steerable filters are combinations of that permit the rapid computation of even and odd (symmetric and anti-symmetric) edge-like and corner-like features at all possible orientations
 - a. derivative of box filters
 - b. derivative of log filters
 - c. derivative of Gaussian filters
 - d. derivative of Gaussian descriptors
- 56.steerable filters are somewhat insensitive to localization and orientation errors
 - a. True
 - b. False
- 57. Feature Matching Components
 - Selecting a matching strategy that determines which correspondences are passed on to the next stage for further processing.
 - b. Devising efficient data structures and algorithms to perform this matching as quickly as possible.
- 58. Determining which feature matches are reasonable to process further depends on the context in which the matching is being performed

- a. True
- b. False

59. number of correct matches.

- a. True Positive (TP)
- b. True Negative (TN)
- c. False Positive (FP)
- d. False Negative (FN)

60. matches that were not correctly detected.

- a. True Positive (TP)
- b. True Negative (TN)
- c. False Positive (FP)
- d. False Negative (FN)
- 61. proposed matches that are incorrect.
 - a. True Positive (TP)
 - b. True Negative (TN)
 - c. False Positive (FP)
 - d. False Negative (FN)
- 62.non-matches that were correctly rejected.
 - a. True Positive (TP)
 - b. True Negative (TN)
 - c. False Positive (FP)
 - d. False Negative (FN)
- 63.In matching strategy and error rates, given an Euclidean distance metric, the simplest strategy is to set a threshold (maximum

distance) and to return all matches from other images within this threshold.

- a. true
- b. false

64.setting the matching strategy and error rates threshold too high results while setting it too low would result

- a. FP, FN
- b. FN, FP
- c. TN, TP
- d. TP, TN
- true positive rate (TPR),

$$TPR = \frac{TP}{TP + FN} = \frac{TP}{P};$$

• false positive rate (FPR),

$$FPR = \frac{FP}{FP+TN} = \frac{FP}{N};$$

• positive predictive value (PPV),

$$PPV = \frac{TP}{TP+FP} = \frac{TP}{P};$$

• accuracy (ACC),

$$ACC = \frac{TP + TN}{P + N}.$$

65..... is how many returned documents are relevant, it is also used instead of PPV.

a.	Precision
b.	Recall
66	is what fraction of relevant documents was found, it is also
used	instead of <mark>TPR</mark>
a.	Precision
b.	<u>Recall</u>
67.A bet	ter approach for reaching an <mark>efficient matching</mark> is to devise an
	, such as a <mark>multi-dimensional search tree</mark> or a <mark>hash table</mark> , to
<mark>rapidl</mark>	y search for features near a given feature.
a.	indexing structure
b.	indexing array
68.One c	of the simpler techniques to implement efficient matching is
	, which maps descriptors into sized buckets based on
some	function applied to each descriptor vector
a.	multi-dimensional hashing, fixed
b.	meat-dragon halal, variable
69.A sim	ple example of <mark>hashing</mark> is the <mark>Haar wavelets</mark>
a.	<u>True</u>
b.	False
70	, Find a set of likely <mark>feature locations</mark> in a first image and to
then	search for their <mark>corresponding</mark> locations in <mark>subsequent</mark> images
a.	Feature detection
b.	Feature descriptor
c.	Feature tracking
d	Feature matching

71.Use in feature tracking, if images are undergoing brightness change

- a. Normalized cross correlation
- b. Hierarchical search strategy
- 72.Use in feature tracking, if the search image is large
 - a. Normalized cross correlation
 - b. Hierarchical search strategy