

Histogram is a 1D vector. It is part of point operations.

gray2gray → ~~map~~ changes the value from 1 to 255 to (0 to 1)

fall - had 3 dhm. (R, G, B)
 (X, Y, Z)

S-4 white, hist \rightarrow over exposed
 mean \rightarrow zero axis = ? (choose $0.5(3, 1, 0, 1, 2)$)

$$\begin{matrix} P_x \\ G \\ Y \end{matrix}$$

$$\begin{matrix} R \\ \nearrow \\ \searrow \end{matrix}$$

$$B$$

black, hist \rightarrow under exposed.
 histogram will cover → man-made man-made.

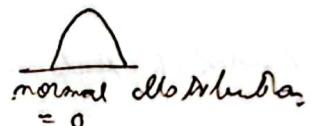
S-17 skewness: measure for distribution / symmetry of hist



negative



right



normal distribution
 $= 0$

Kurtosis: measure of flatness / peakness



$k < 0$ low
 platy-

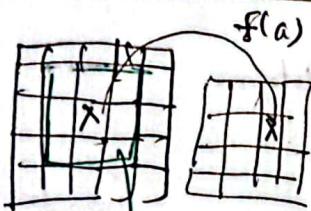


$k = 0$
 normal distribution



$k > 0$
 very leptotic

P-20



Find 8 other methods

pixel vs. top depends

and pixel ^{center}, update

$f(x)$

Project (Instead of exam)
 MON → guess FRI last week
 FRI → submission of classes

grade A to F

project with report

1+ Day of work

but will take 5 days

Histogram is a 1D vector. It is part of point operation.

gray → ~~var~~ changes the value from 1 to 255 to (0 to 1)

full - bad 3 dim. (R, G, B
 X, Y, Z)

S-4

(for white, hist \rightarrow JAF250 refer to → over-exposed

mean starts. Turn axis = ? (or choose $T.0(3, 1)$, $(0, 1, ?)$)

$$\begin{matrix} R \\ G \\ B \end{matrix}$$

(for black, hist \rightarrow ~~var~~ refer to → under exposed.

Histogram will coarse → man-made man-made.

S-17 Skewness: measure for distribution / symmetry of hist



negative

< 0
left



positive. > 0

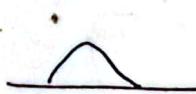
right



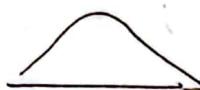
normal distribution

$$= 0$$

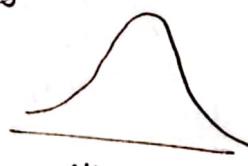
Kurtosis: measure of flatness / peakness



< 0 low
platy-

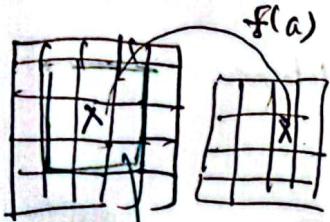


$= 0$
normal distribution



> 0
very leptotic

P-20



fixed & same weight

pixel vs top depend
top pixel ^{earlier} update

2nd

Project (Instead of exam)
MON → give f5(3) last week
FRI → submission of classes

grade A to F

project with report

1+ Day of work

but will give 5 day

S-25

THRESHOLDING → for this histogram will
be just 2 bars.

$$f_{\text{threshold}}(a) = \begin{cases} a_0 & \text{for } a < a_H \\ a_1 & \text{for } a \geq a_H \end{cases}$$

Also - very common → HW 1

P-31 by modifying the histogram → you can increase the
contrast.

→ useful for low quality images

P-32 Automatic contrast. → make the lowest to 0] stretching
make the highest to 255] linear transformation

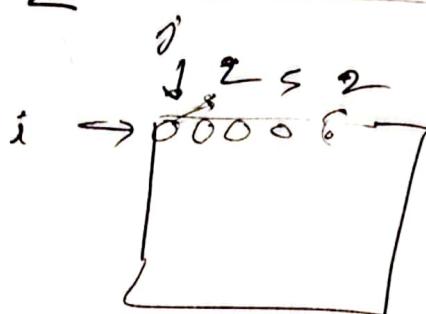
P-34 Modified automatic contrast adjustment.

low = 0, highest = 255. saturated pixels → count them
count max → in man & high
deformation.

1-ss camera sees exactly the same light
humans see linearly.
input image enters low &
extreme high lights
and ratio
ratio!

0 = col

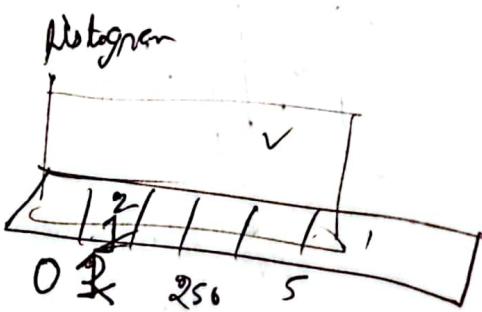
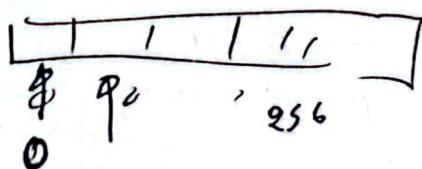
1 = row



③

n-1

cumulative



S-25

THRESHOLDING → for this histogram will
be just 2 bars.

$$f_{\text{threshold}}(a) = \begin{cases} a_0 & \text{for } a < a_H \\ a_1 & \text{for } a \geq a_H \end{cases}$$

Also - very common → HW 2

P-31 by modifying the histogram → you can increase its contrast.

→ useful for low quality images

P-32 Automatic contrast: → make the lowest to 0] stretching
make the highest to 255 [linear transformation

P-34 Modified automatic contrast adjustment.

low = 0, highest = 255. saturated pixels → gray map

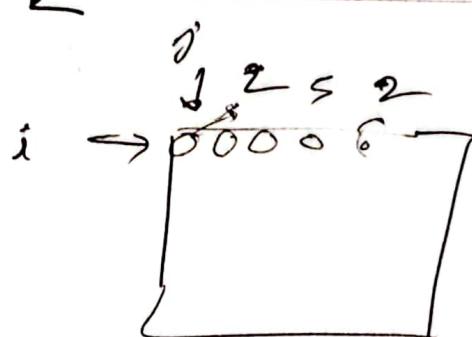
count max in man & high

determination.

→ camera sees exactly linear light
humans are linearly.
→ man sees extremely low &
extreme high lights
"very diff.",
axis!

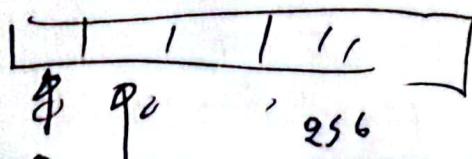
0 = cd

1 = now

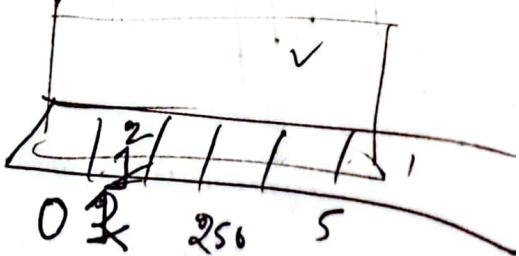


★

^1 curvilinear



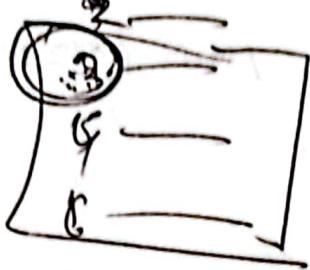
Histogram



der
 $N = 3$ LAB 3

$$6 - 3_0 = \underline{3+1} = \textcircled{4}$$

$$\begin{array}{r} 5 \\ 6 \end{array}$$

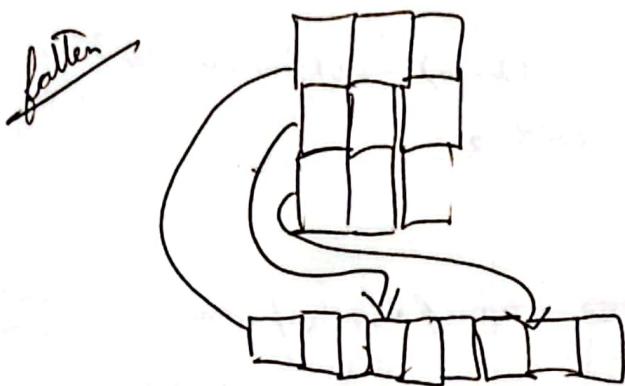


~~will another~~
~~is reduced~~

$$N = 10$$

$$\text{start } (10-3) = \textcircled{7}$$

$$\frac{\text{loop}(3)}{\text{start}} = 89 \quad 10$$



pk image.
 equalizeHist

`plt. subplot(1, 1, plt.imread('lenna.png'))`

\rightarrow big image

pk image exposure.

~~shift~~ ~~shift~~

`equalizeHist()`

MAX $\frac{30}{255}$

$$\frac{5}{\textcircled{5}}$$

$$\textcircled{25}$$

$$-5 + 30 = 25$$

`bin_edges[0:-1]` $\begin{pmatrix} 4 \\ 6 \end{pmatrix}$
 original

`plt.plot(edges, histogram)`



Point operation → all operation is done for 1 pixel.

Filter operation → works on several pixels. (3×3 pixel)

→ most important. (Window size).

smoothing → mean filter

filter → 2 type: linear, non-linear.

Linear filters:

duplicate

process-filters - convolve (linear) → 5×5 → window
→ it will give edges with 24.

Gaussian filters:

more pixel → 7×7 into → σ^2 of blurring/smoothing value.

Linear filter

① commutativity: I-image, H-filter.

② linearity → scale numbers.

③ associativity → B, C → filters.

④ separability (X/Y)

$$H_x = [1 \ 1 \ 1]$$

$$H_y = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$H_{xy} = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

blurred image
does not have
the edges.
so when you subtract
it with the original
you get the edges.

Analyzing residual image: / After blurring contrast points are gone.

image calculator → operation → subtract.

for enhancing image → also histogram.

edge detection

residual = ^(blurred image) filtered image - original image = will give blur edges
→ use equalized histogram for getting the proper edges

L-3 (Filter)

Point operation → all operation is done for 1 pixel.

Filter operation → works on several pixels. (3×3 pixel)

Green → most important. (Window size).

Smoothing → mean filter

Filter → 2 type: Linear, non-Linear.

Linear filters:

duplicate

process - filters - convolve (Linear) → 5×5 → window
→ it will give edges with 24.

Gaussian filter:

more pixel → $\text{filter} \rightarrow \text{avg} \rightarrow \text{avg}$ of blurring/smoothing value.

Linear filters

① commutativity: $I \rightarrow \text{image}, H \rightarrow \text{filter}$.

② linearity → scale numbers.

③ associativity → $B, C \rightarrow \text{filters}$.

④ separability (X/Y)

$$H_x = [1 \ 1 \ 1]$$

$$H_y = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$H_{xy} = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

blurred image
does not have
the edges.
so when you subtract
it with the original
you get the edges.

Analyzing residual image: / After blurring contrast points are gone.

image calculator → operator → subtract.

for enhancing image → also histogram.

edge detection

residual = $\begin{matrix} \text{blurred image} \\ \text{filtered image} \end{matrix} - \text{original image} \Rightarrow \text{will give blur edges}$
→ use equally histogram for getting the proper edges

not-linear filter:

mean - linear

median \rightarrow non-linear.

linear filters will ignore
the borders. (not true for
non-linear \rightarrow does not)

Borders:

non-linear filter (non-linear function \rightarrow maximum, minimum filter)

\rightarrow better

salt-pepper \rightarrow 0 & 255 add.

mean of 11245

$\frac{5}{13}/2^C$

11 11 11
11 11 11
11 11 11

11 11 11
11 11 11
11 11 11

non-linear median filter \rightarrow does not work

letter image

\rightarrow add noise \rightarrow add salt & pepper. \rightarrow use median filter for smoothing & removing noise.

(a)

0	1	1	0	0
1	0	0	1	0
0	1	0	0	1
0	0	1	0	0
0	0	0	0	0

0	0	0
0	0	0
0	0	0

(b)

0	2	6	6	0
0	1	0	0	0
0	2	0	0	6
0	1	0	0	0
0	0	0	0	0

0	0	0
0	0	0
0	0	0
0	0	0

always less than 9
 \rightarrow 5 or 0

0	0	0
0	2	0
0	0	0

0	.	.
0	.	.
0	.	.
0	.	.

\rightarrow median \rightarrow 0
 > 4 1's \Rightarrow 1
for being 1

0	0	0
0	0	0
0	0	0

(c)

0	0	0
0	2	0
0	0	0

0	0	0
0	1	1
0	0	0

0	0	0
0	1	1
0	0	0

(d)

1	0	*
0	2	2
0	2	2

0	0	0
0	2	0
0	0	0

always less than 4
 \rightarrow 5 or 0

Not/Blurry filter:

[mean-blur
median → non-blur]

linear filters will smooth
the boundaries. (not true for
non-linear, → does not)

Border:

non-blur filter (non-linear function → median) → non-linear filter
salt-pepper → 0 & 255 added.

mean of 11245

11 2 9 5

$\frac{5}{13}/2^{\circ}\text{C}$

non-blur median filter → does not smooth

letter image

→ add noise → add salt & pepper. → use median
filter for smoothing & removing noise.

2	1	1	1	.
1	0	0	1	.
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0

always less than
or equal to 0

6	2	6	6
0	1	0	0
0	3	0	6

0	0	0
0	0	0
0	0	0

0	0	0
0	2	0
0	0	0

0.
0.
0.
0.
0. → median → 0
0.
0.
0.
1. > 4 1's means
for being 1

(c)

0	1	1	0
0	2	1	0
0	1	1	0

0	0	0
0	1	1
0	0	0

0	0	0
0	1	1
0	0	0

(d)

0	0	0
0	2	2
0	2	2

0	0	0
0	2	0
0	0	0

always less
than 4
or equal to 0

Non-local means: → important for finding patterns in data

repetitions → some similarity.

average neighboring → images

always same pixel, but different noises.

noise = N^2 → for average, σ (ref) noise same R^2 , same, noise different

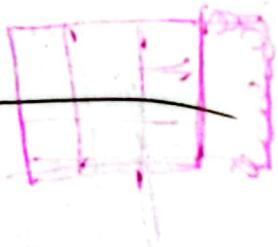
→ reduce noise by average.

for similar neighborhood, find the average, then replace it for all pixels, R^2 picture center. best average option: look for mean square error.

Replace the pixel by average.

Difference → creates edges.

sobel → used for edge detection



Hyper-spectral images

Remote sensing → camera, scanner (satellite, satellite, planes, drone, use for)

Active → no external source (LiDAR) camera

Passive → need external illumination (hyper-spectral sensor)

RGB camera of phone → with flash → passive
without flash → active

more info
in flash case



Non-local means: → important for finding patterns in data

repetitions → some similarity.

average neighboring → images

always same pixel, but different noises.

noise = N^2 → for average, so (P_1) noise same R^2 , same noise different

→ reduce noise by average.

for similar neighborhood, find the average, then replace it for all similar pixels R^2 center.

best average option: look for mean square error.

Replace the pixel by average.

difference → creates edges.

sobel → used for edge detection

Hyperspectral images

Remote sensing → camera, scanner (satellites, planes, balloons, etc.)

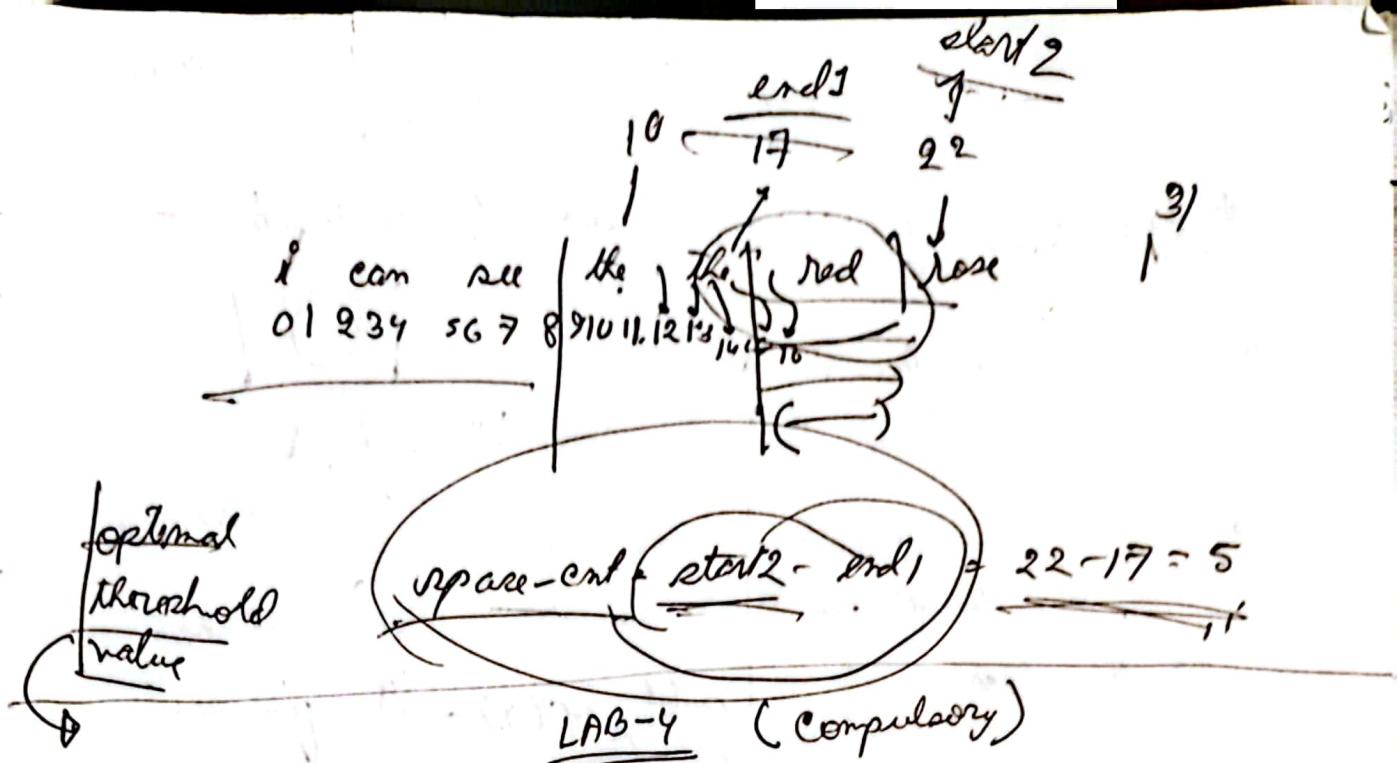
Active → no external source (LiDAR) camera

Passive → need external illumination (hyperspectral sensor)

RGB camera of phone → with flash → passive
without flash → active.

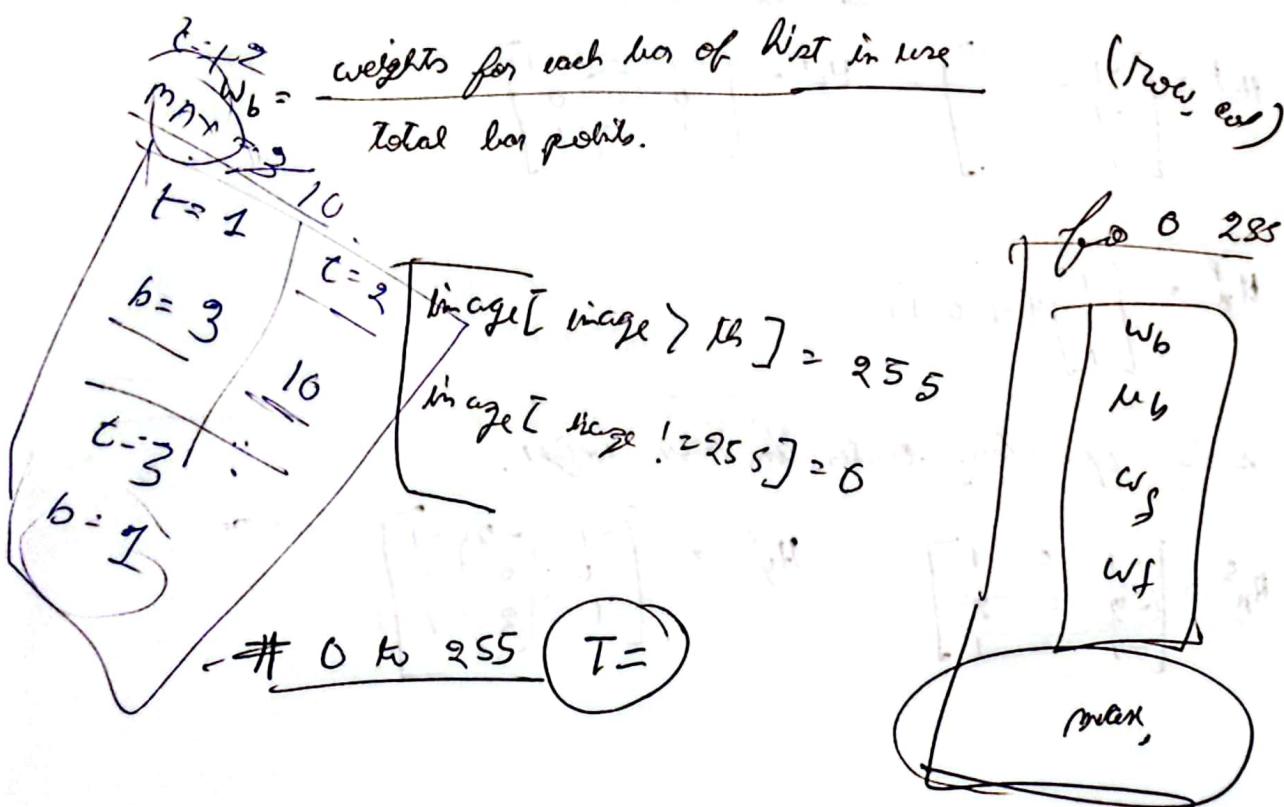
without flash
= global avg





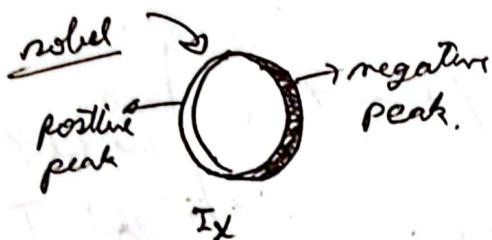
within class variance \rightarrow min. / lowest.
 between classes variance \rightarrow MAX
 are called get T

Ques. Should the image be changed to gray?

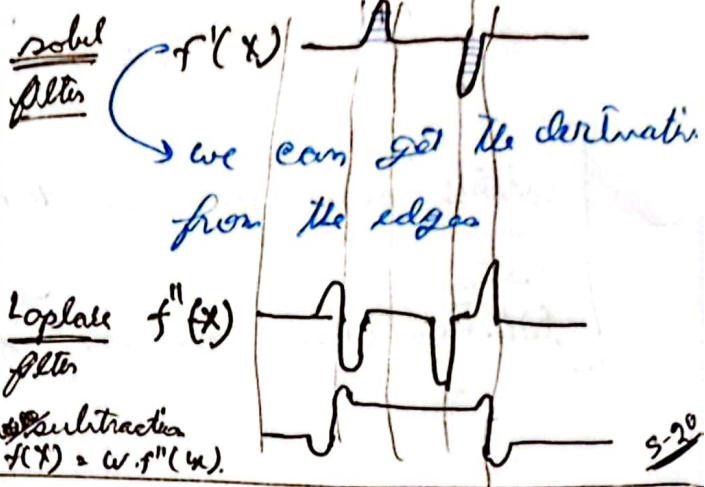
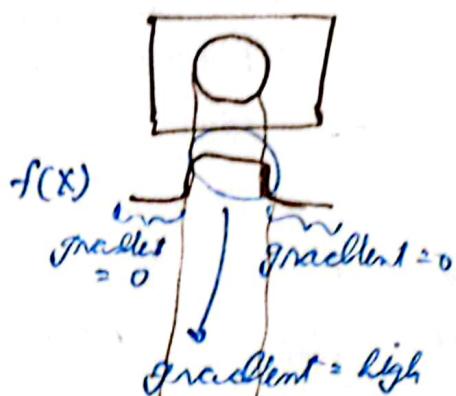


L-4 (Edges & Contour)# Edge detecting Filters:

- # Checking derivatives in both the directions.
- # magnitude of derivative will give the strength of the edges



$$H_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \quad H_y = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

intensity distribution

gradient Filter: → gives result same as computing gradient.

prewitt operator → equal weight to all the pixels

$$H_x^P = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad H_y^P = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$H_x^P = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \times [-1 \ 0 \ 1]$$

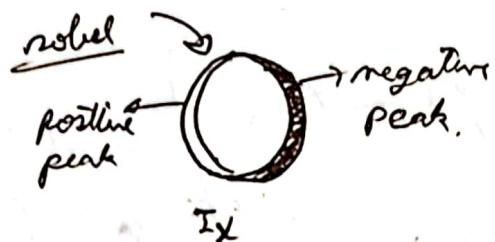
Sobel operator: center line more weight.

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

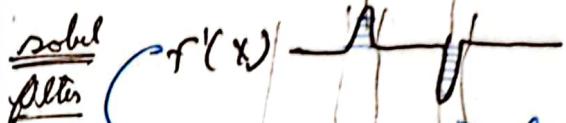
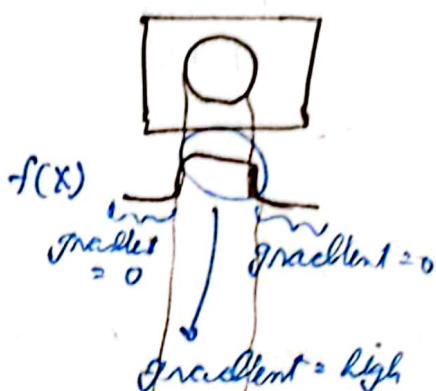
L-4 (Edges & Contour)# Edge Detecting Filters:

Checking derivatives in both the directions.

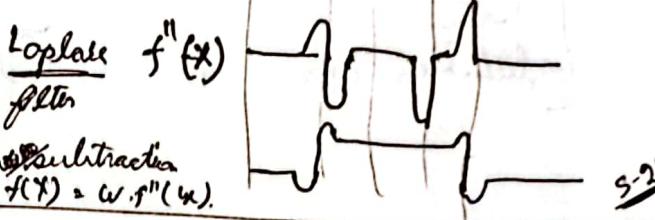
magnitude of derivative will give the strength of the edges



$$H_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \quad H_y = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

intensity distribution

we can get the derivative from the edges



gradient Filter: → gives result same as computing gradient.

prewitt operator → equal weight to all the pixels

$$H_x^P = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad H_y^P = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$H_x^P = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \times [-1 \ 0 \ 1]$$

Sobel operator: center line more weight.

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

∇g \rightarrow to similar to taking the mean.

sobel \rightarrow will show combined ∇x & ∇y (showing edges)

sobel-h \rightarrow horizontal:

sobel-v \rightarrow vertical!

prewitt \rightarrow also combines horizontal & vertical.

\rightarrow cannot do it separately, like sobel.

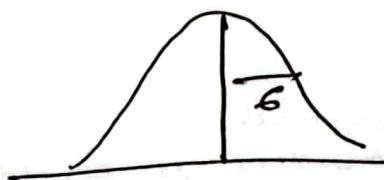
we can composite both magnitude & angles. for SOBEL.

Canny Filter (popular) \rightarrow complex & efficient in terms of noises & sharp lines which are no edges.

1st smoothing filter (Gaussian)

then sobel

Then thresholding



hysteresis thresholding

\hookrightarrow how the lines are connected.

Gaussian filter.

σ = amount of smoothing

Read from openCV \rightarrow tutorial - py - canny. Pdf.

below minimal \rightarrow not a edge
over maximal edge.

by default min -10,
max -25
 \rightarrow 20 \checkmark user
Check.

increase contrast - sharpness \rightarrow increasing the intensity of edges.

removing false edges:
maxval [] \rightarrow what edge
minval [] or not.

smoothing
Gaussian -> intensity of blur
sobel
sigma

filter one \rightarrow convolution

$$h_x = [1 \quad -2 \quad 1]$$

$$h_y = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

$$H^L = H^{\text{Laplace}} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$f'(x) \text{ vector} = f(x) - w_i f''(x)$$

original image weight 2nd derivative
 ↓ ↓ ↓
Laplace \rightarrow pos & neg image $f''(x)$

$$\text{active} - 1 \times \text{neighbor}$$

↓ ↓
f(x) f'(x)
can be more
than 1.

applying filter is like convolution.

FI \otimes L (image)

→ column

→ make 8 bits (image-type)

→ process \rightarrow filter

→ convolution (edge)

process contrast → improve contrast

→ need to find histogram.

enhance contrast
→ equalize histogram.
(stretched histogram)

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

matrix for each convolution

mean filter is considered as low pass filter.

mean filter (low pass) \rightarrow sharp variations will be smoothed out.
only passing low variation

high pass filter \rightarrow enhance structure. (Only passes sharp variation)
edges.

looks similar to
highpass:

image 3 $\begin{cases} \# \text{image} - \text{gaussian blur.} \rightarrow \text{subtract} \rightarrow \text{original} - \text{gaussian} \\ \text{with sigma 5} \quad \text{image calculator} \end{cases}$
enhance contrast \rightarrow sharpen. (process \rightarrow enhance contrast
 \rightarrow equalize)

image 2 image 3

filters are → convolution

$$H_x = [1 \quad -2 \quad 1]$$

$$H_y = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

$$H^L = H^{\text{Laplace}} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$f''(x)$ ~~filters~~ = $f(x) - w \cdot f''(x)$

original img. weight 2nd derivative
↓ ↓ ↓ Laplace

Laplace → pos & neg image $f''(x)$

$\text{active} - 1 \times \text{astrolap}$

↓ weight ↓
 $f(x)$ can be more
 than 1.

applying filter is like convolution.

FI TI (image)

↓ down

→ make & edit (image-type)

→ process → filter

→ convolve (edg.)

Process Enhance
contrast contrast

→ improve contrast
→ need to fix
histogram.

0 1

enhance contrast
→ equalize histogram.
(stretched histogram)

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

matrix for convolve
convolution

mean filter is considered as low pass filter.

↓ mean filter (low pass) → sharp variations will be smoothen out.
only passing low variation

high pass filter → enhance structure. (Only passes sharp variation, edges.)

looks similar to
highpass

↓ original image - low-pass-filt.

Image 2 image?

image - gaussian blur. → subtract → original - gaussian
with sigma 5 image calculator

image 3

↓ enhance contrast → sharpen. (process → enhance contrast
→ equalize)

un-sharpen mask (USM) → similar to high pass filters. → for increasing sharpness using edge detection.

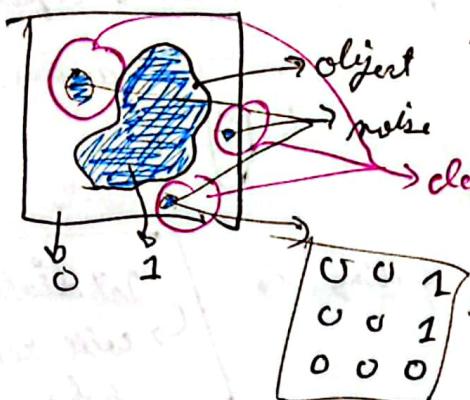
$$M = I - \bar{I}$$

M ← original - smoothed ($I \times H$) \bar{I}
(ANS) I image by kernel
distance
distance for pixels in gray value.

- topics
- ① smoothing
 - ② noise reduction
 - ③ edge detection
 - ④ sharpening
 - ⑤ morphology

amount = factor a = parameter → weight.
→ sharpen using USM. (a is the sharpening weight)

always define algo → parameters of your work.



morphology → get rid of noises.

①

depending on the threshold, it will remove the noises

→ min-val = 0

- ① Apply MIN → remove noises
- ② Apply MAX → will return object

LAB-5

imread (asarray = true)

imshow (water, ! hot!)

amount = 2

imread (— , ! hot!)

L5 (Morphology) → Wholly both
 → grey } Images.
 → filter use.

11.10.22

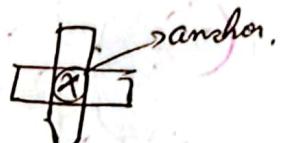
change the shape of object. | using morph filters.
 (shrinking & removing noise. | C smooth edge, shrink object.

morph filters use to grow the object.

Removing holes. $I \ominus H$ or $I \oplus H$ or $I \ominus H \oplus H$

erosion (shrink) - Min anchor point → center of a pixel

dilation (grow) f Max filters
 bright part → \oplus anchor point → change anchor pixel.



grow dilation [square → 8 neighborhood.]

maximum value selecting. holes are filling in.

1st dilate
 will remove holes

→ then shrink
 go to original without hole

erosion (shrink)

Image J 1st edit - invert
 process binary → erode → invert
 " P " → dilate →

Image J Invert
 black → object (foreground)
 white → background.

Contours:



shrink
 erode
 removed
 edge
 find



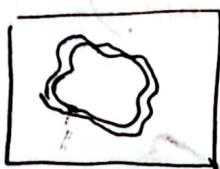
or open
 union

$I \ominus H$
Invert



2nd shrink
 will remove hole
 or noise
 then grow

contours = $I \ominus H$



Binary image

0 → background (black)
 1 → foreground (white)

dilate - object \oplus
 and > layers pixel

shrink → object \ominus last pixel χ_{not} identify χ_{not}
 contrast to background. Then remove.

add \oplus (object grow)

opening \rightarrow eroding \rightarrow dilation] for cleaning the image.
closing \rightarrow dilation \rightarrow eroding
 \hookrightarrow for reducing holes.

jpeg \rightarrow lossy compression

opening: Image J

- 8 bit image
- \hookrightarrow select the part \rightarrow crop
- \hookrightarrow process \rightarrow adjust \rightarrow threshold \rightarrow others
- \hookrightarrow library \rightarrow closing (multiple times)
 - \rightarrow invert
 - \rightarrow fill holes ($\overset{\text{plate}}{\text{will fill multiple of time until fill}}$)

1-line skeleton of image

looks at background of the object (considers black as object)

If gray image \rightarrow more weight to center pixels.

[13.10.22]

L-G

open \leftarrow close .

T-2

canny filters \rightarrow edge detection

Invert

canv - 6 = 1

canv 6 = 3

Invert

T-3

median filter (sharpen)

closing on opened image.

for a b object: pixels should be connected to each other.

2 methods:

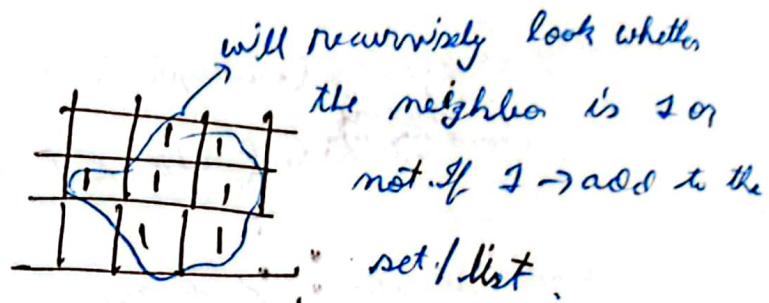
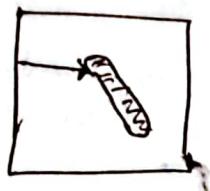
① flood filling → recursive function.

② sequential region marking

old/classical process.

Flood fill:

S-8



S-9

Inner & outer contours:

→ Run length encoding

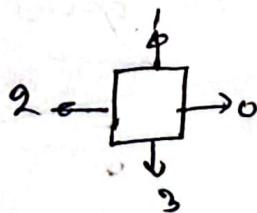
- uses lot of data compression.

matrix → to RLE (row, col, length) [compressed way]

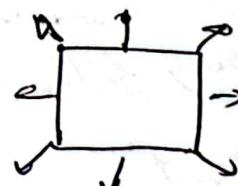
S-11

Chain code!

4-chain code.



8-chain: also has the diagonals



2 objects can have same area, but not perimeter.

S-16: Moments: axis changing might be useful for detecting an object.

Real moment:

$$M_{10} = \sum_x \sum_y x^i y^j I(x, y) \rightarrow \text{when it is containing the object, } \rightarrow \text{all will be 1.}$$

$$M_{00} \rightarrow \text{Area.} \quad \begin{matrix} \text{binary image is 1} \\ \text{while gray is 0} \\ \downarrow \text{gray image is intensity} \end{matrix} \quad \bar{x} \rightarrow \frac{M_{01}}{M_{00}}$$

Central moment: $\bar{x} = \frac{M_{10}}{M_{00}}$

Image J:

Sample \rightarrow blob \rightarrow [processes \rightarrow binary \rightarrow make library.] \times

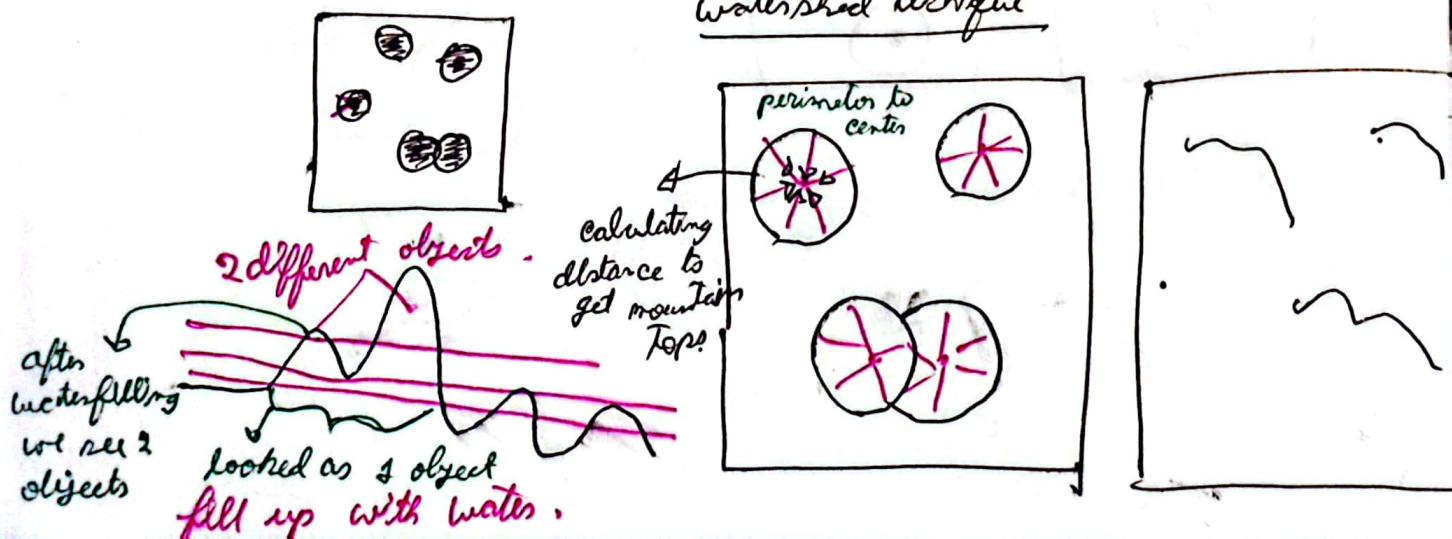
Image \checkmark \rightarrow adjust \rightarrow auto-threshold \rightarrow other small noise gone.

Analyze \rightarrow Analyze particles \rightarrow size [50 - infinity] \downarrow
if 0 (small objects will be added)

Analyze \rightarrow set measurement \rightarrow ① Area, ② cent of mass, ③ shape descriptors

④ perimeter, ⑤ Feret's diameter, ⑥ Euler

Watershed technique



2 objects can have same area, but not perimeter.

S-16: Moments: axis changing might be useful for detecting an object.

Real moment:

$$M_{ij} = \sum_k \sum_f x^i y^j I(x, y) \rightarrow \begin{array}{l} \text{when it is containing the object - all will be 1.} \\ \text{binary image into} \\ \text{black white gray pixel} \end{array}$$

$$M_{00} \rightarrow \text{Area.} \quad \downarrow \text{gray image - intensity pixel}$$

Central moment: $\bar{x} = \frac{M_{10}}{M_{00}} = \bar{y} = \frac{M_{01}}{M_{00}}$

Image J!

sample → blob → [process → binary → make binary.] X

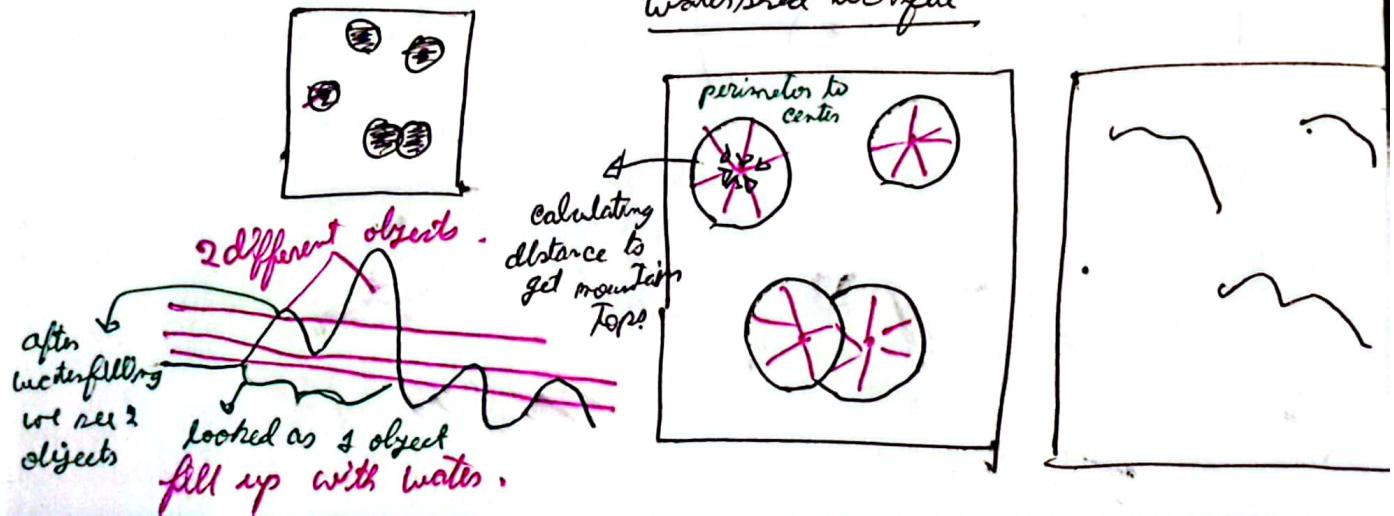
Image / → adjust → auto-threshold → other small noise gone.

Analyze → Analyze particles → size [50 - slightly]
if 0 (small objects will be added)

Analyze → set measurement → ① Area, ② center of mass, ③ shape descriptors

④ perimeter, ⑤ Feret's diameter, ⑥ Euler

watershed technique



ImageJ!

blob → binary → make library
→ distant map

Now it is
in segmentation
package.

distant Plugin Analyze → 3D surface plot.
map
last one is the water levels.

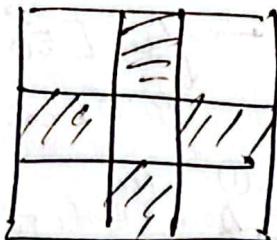
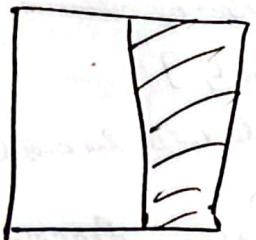
binary watershed (On the binary image,

S-32

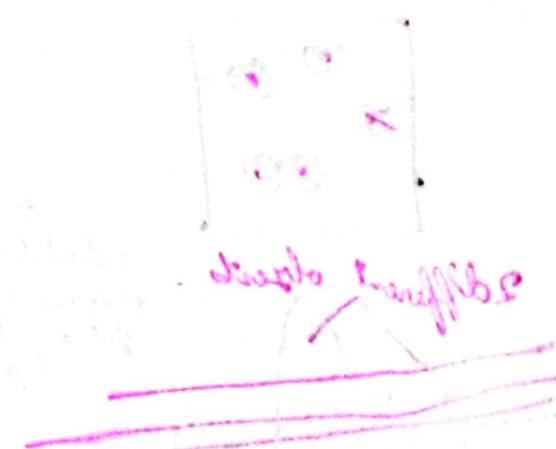
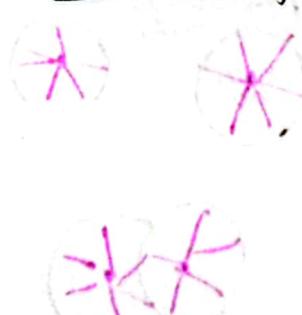
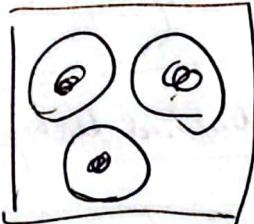
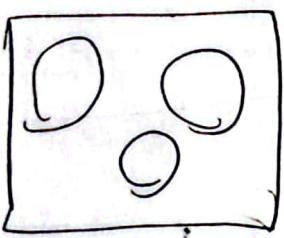
make a mask

binary image. (object → black
background → 0)

mask = binary + original (background gone)



} different texture
but same area



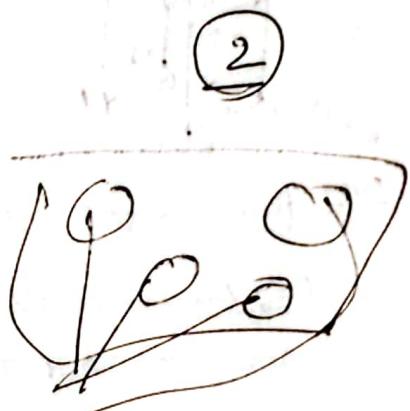
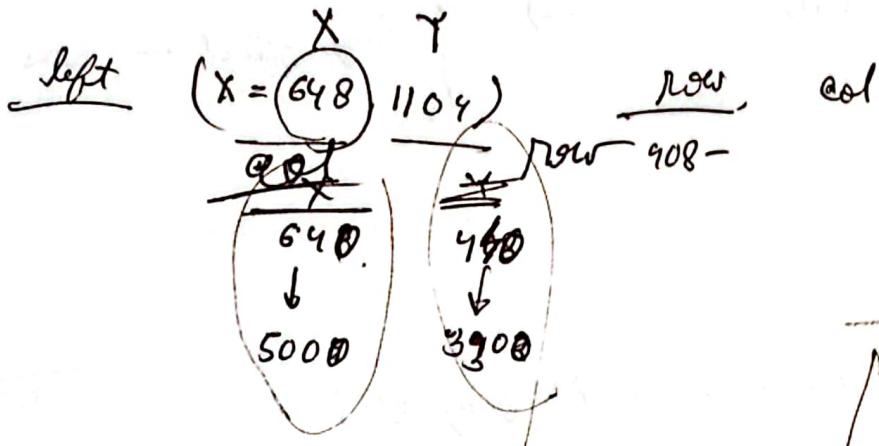
full LHS col $\rightarrow 0.7$ row $\rightarrow 0.9$ non-stop

diff

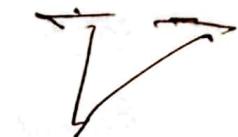
X Y

$$\begin{array}{r} 1279 \\ 1671 \\ 1583 \end{array} \quad \begin{array}{r} 1171 \\ 1671 \\ 1444 \end{array}$$

non-stop \rightarrow round
18m \rightarrow longer.



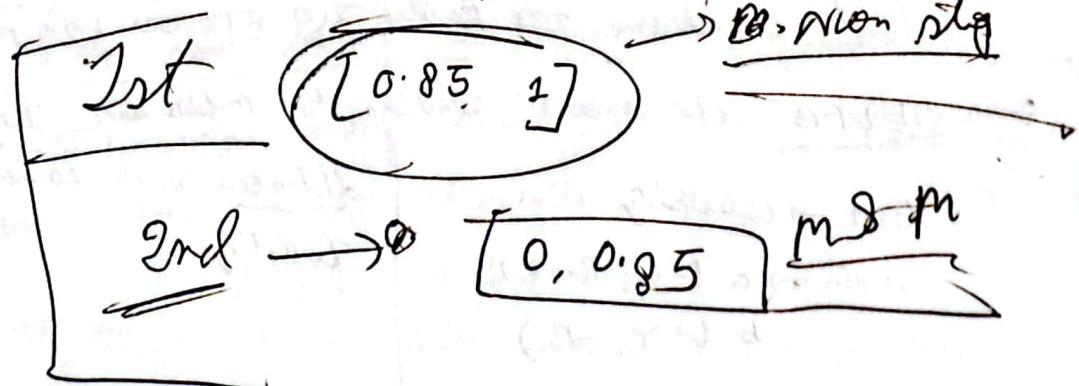
- ① \rightarrow maxima
use maximum \rightarrow fills
making rounder
- ② \rightarrow cols.



Area \rightarrow center of mass

decimal places \rightarrow 3 to 5.

coordinates will be \rightarrow 0 to 1 \rightarrow most round

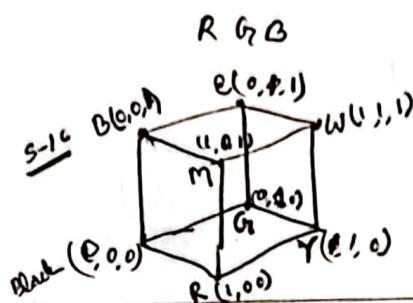


L7

Color Images

→ defined for R, G, B
CIE → international commission on illumination
CIE → horseshoe → colors on edge are unique colors.
 eye sensitivity → Red → green → blue
 (H) (M) (L)

compression vs time
 green & blue parts
 CMYK don't have huge effect on eyes



S-10. Here: → some colors are gray so.

Brightness → emitted light per area. part-a
 part-b

Gray = $\frac{R+G+B}{3}$

Lightness → value or tone of color.

Chroma → measure of purity of a color.

Gamut → complete subset of colors within a color space.

→ All colors available within a color-space.

S-12 RGB primary additive colors: mixture of primary RGB → used in monitor
 part-b model CMY subtractive colors: mixture of CMY cyan, magenta, yellow
 secondary colors → used in printers, cameras.

S-13 # Munsell Color System: → color modeling part-a → use part-b
 - brightness → intensity.
circle → hue.

Radius → chroma, π radius 2(0 170 30) (more pure (purity))

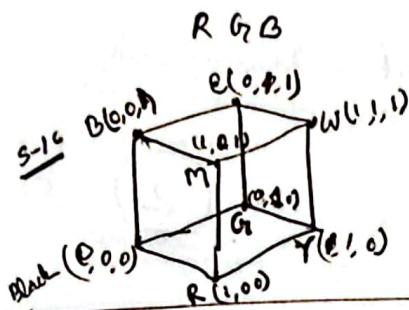
S-20 CIE LAB color model: similar to munsell. They use delta distance much easier to quantify.
 B or → intensity.
 a axis → a (-G, R → +)
 b axis → (+Y, -B)

L7Color Images

defined for R, G, B

CIE → international commission on Illumination

CIE → horseshoe → colors on edge are unique colors.

eye sensitivity → Red → green → blue
(H) (L)compression vs time
green & blue zero
DPIs don't have huge effect on eyesS-10. Hue: → same color -> same hue & gray value
Brightness → irradiated light per area. part-a
part-b applies to it
Lightness → value or tone of color.Chroma → measure of purity of a color.Gamut → complete subset of colors within a color space.

→ All colors available within a color-space.

S-12 RGB! primary additive colors: mixture of primary RGB → used in monitor

CMY subtractive color: mixture of CMY cyan, magenta, yellow
secondary colors → used in printers, devices.

S-13 # Munsell Color System: → color modeling vs 3D → use 2D
- brightness → intensity.
circle → hue.

Radius → chroma, 00 radius 20 50 70 90 (for pure (purity))

S-20 CIELAB color model: similar to munsell. They use delta
B or → intensity.
ants → a (-G, R→+)
b (+Y, -B)

distance much easier to quantify.

Image J: (Masked out image) specular reflection \rightarrow 0% holes 2%
 select \rightarrow crop
 image \rightarrow duplicate.
 image \rightarrow type \rightarrow 8 \rightarrow binar
 enhance contrast \rightarrow hist equalization
 \rightarrow make binary
 process \rightarrow fill holes.

0 \rightarrow background
 256 \rightarrow object.

Invert \rightarrow for making mask

(0 \rightarrow background, 256 \rightarrow object)

Image \rightarrow Add \rightarrow original + mask

* Image works with wavelengths not colors.

split channel

image \rightarrow color \rightarrow split channel

In. Red image \rightarrow Red \rightarrow white, green/black \rightarrow black.
 yellow \rightarrow most light.

Convert to LAB

Image \rightarrow color \rightarrow RGB to CIELAB (for just grey img 100%
 50% str 50%)

image \rightarrow type \rightarrow LAB stack

image \rightarrow color \rightarrow split channel. (white - L)

area - A (red & green)

Red light) gray \rightarrow black

area \rightarrow B (blue \rightarrow yellow \rightarrow white)

5-25 Gamut: triangle is called color gamut \rightarrow min & max will get your color. also inside the gamut \rightarrow 50% not possible

color \rightarrow 11 edge \rightarrow Gamut - 4.7 ed 2 - edge point

4.7 mixture func. Chromaticity diagram - 4.7 3 colors
 \rightarrow 361 colors

Triangle - 4.7 edges natural colors monitor \rightarrow 75% not 7%

Image J: (Masked out image) specular reflection \Rightarrow TPS
holes \Rightarrow I

select \rightarrow crop

image \rightarrow duplicate.

image \rightarrow type \rightarrow S \rightarrow blur

enhance contrast \rightarrow histogram equalization
 \rightarrow make binary

process \rightarrow fill holes.

0 \rightarrow background
255 \rightarrow object.

Invert \rightarrow for making mask

(0 \rightarrow background, 255 \rightarrow object)

original \rightarrow Add \rightarrow original + mask

~~Invert works well with monochrome not colors~~

split channel

image \rightarrow color \rightarrow split channel

Im. Red image \rightarrow red \rightarrow white, green/black \rightarrow black.
Yellow \rightarrow most light.

Convert to LAB

image \rightarrow color \rightarrow RGB to CIELAB (~~for just grey \Rightarrow FTS~~
~~so str. m~~)

image \rightarrow type \rightarrow LAB stack

image \rightarrow color \rightarrow split channel. (white - L)

area - A (red & green)

red light) green \rightarrow black

area \rightarrow B (blue \rightarrow yellow \rightarrow white)

S-25 Gamut: triangle is called color gamut \rightarrow min & max will
get your color. ~~so~~ inside the gamut \rightarrow ~~so~~ possible

color ~~min~~ edge chromatic gamut - \Rightarrow 2-edge point

\Rightarrow min area face, R chromatic diagram - \Rightarrow 3 colors

\rightarrow 3 by 3 colors

Triangle \rightarrow ~~so~~ natural colors monitor \rightarrow ~~so~~ \Rightarrow TPS

database of different textures.

intensity variations give no texture.

Texture analysis → textures on different part of body.

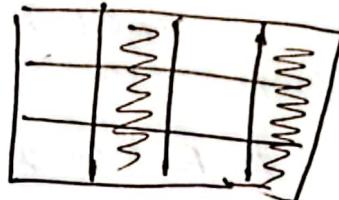
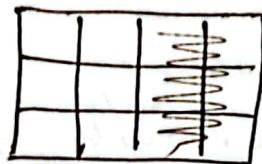
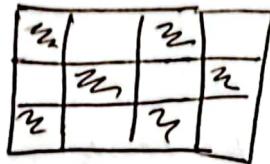
Histogram gives info about texture.

Scale → is important. B/W / gray to image → org. text. depend
on complete different textures.

texture feature extraction: 2 methods

textures

method 1: ① using histogram (1st order statistics) $\left\{ \begin{array}{l} \text{mono color} \\ \text{color} \end{array} \right.$



Prob: In histogram → all 3 patterns will be same, but they are not.

Solution:

histogram of small parts of the image.

method 2: ② Co-FCM: looks at neighboring pixels at small levels.

looks at co-occurrence of different neighbor pixels.

→ looks at according to angle. (0° → side-side, 45° → diagonal)

gives values for each texture. make a image with the texture values.

(color & texture) to distinguish between stuff.

threshold according to gray level co-occurrence.

Texture & color both important for distinguishing objects

Assignment - 02

footprint → change the filters.

roughness / bumpiness refers to variations in intensity / gray levels.

texture analysis: useful when objects are characterized by their texture.

Compared to intensity.

Traditional thresholding does not work for this.

LDA

① Crop → 8 bit → process → enhance contrast (hist eq) → binary → fill holes.

import in Fiji

② Invert (object → black, background → white)

0 → in object (black)

③ add original + mask

255 → background

(image) only the objects

④ RGB image to split; image → color → split channel.

× blue → all black → red (green-black = black, yellow-white), green

RGB to LAB: RGB to CIELAB (1 gray scale image) X

✓ image-type (LAB stack) → split channel (works) ↗ cannot split this

✓ image → color → RGB to CIELAB (B → AHS)

cannot split this

LAB (1 gray image)

Image → transform

Image LAB stack → take B → image → adjust → threshold →

black & white

highlight the object

Texture & color both important for distinguishing objects

Assignment - 02

footprint → change the filter.

Roughness / bumpiness refers to variations in intensity / gray levels.

texture analysis: useful when objects are characterized by their texture.

Compared to intensity.

Traditional thresholding does not work for this.

LDA

① Crop → 8 bit → process → enhance contrast (hist equal) → binary → find holes.

Import in Fiji

0 → in object (black)

255 → background

② Invert (object → black, background → white)

③ add original + mask

(magical)

only the objects

④ RGB image to split: image → color → split channel.

✗ blue (all black) → Red (green-black = black, yellow-white), Green

RGB to LAB: RGB to CIELAB (1 gray scale image) ✗

✗ image-type (LAB stack) → split channel (works) ↳ cannot split this

✗ image → color → RGB to CIELAB (B → AHS)

cannot split
this

LAB (1 gray image)

Image → transform

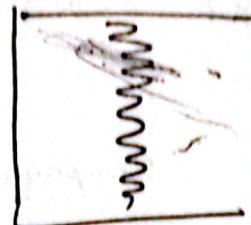
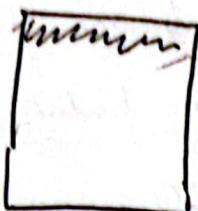
Image LAB stack → take B → image → adjust → threshold →
black & white

highlight the object

L9GLCM Texture Features

Histogram → says info about dark & grey.

Different textures can have same histogram.



Histogram same,
but texture different.

Code from skimage

img as_float() → float to 8 bit image.

Multivariate Analysis

chemo-matrix → look at data in observational way.

Find patterns in the data.

Hogogram → he wrote most used PCA algorithms

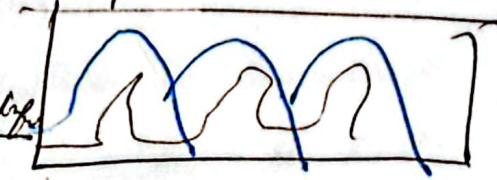
PCA can be programmed in different ways.

Nipals is one of the ways

PCA → is the way of finding data with large variation

small spectral variations cannot be captured in a image.

Green plants reflect in near-IR
 so without the filters → we will not see the original color.



lot of info about the materials in Infrared

S-5

Multi-spectral imaging: more than 3, up to 10 discrete bands in a image.

Hyper-spectral analysis → for finding rotten veg.

Hyper-spectral images → usually have more than 3.

λ = wave length.

NEO → gives best high spectral camera
 spectrum, \rightarrow swedish company.

Line-scan camera:

active sensor: the camera is → passive.

but using it is active.

$$NDVI = \frac{NIR - R}{NIR + R}$$

] -1 to 1
 (-2 to 0) → not vegi
 (0.2 - 1) → clearly vegetation

Phenotyping:

plant breeding → increase production.
 → making crops adaptable to environment.
 → genome testing for finding the best.
 ↳ cross phenotyping

visual selection → sensors
 → genetic markers.

Active sensors → GreenSeeker
 → SPAD

passive sensors → dark reference
 → white reference.
 → cameras

① XRAY
 low energy → longer wave length. (used for checking the roots)

② Visible ↳ blue → shortest wave length.

③ IR → After Red → not visible by eyes → uses spectroscopy.

④ Thermal → uses different cameras.

Spectroscopy: → measures different pigments.
 → used for detecting stress.

High-spectral imaging: each plant contains multiple info.
 → no of wavelength usually less.

Thermal camera → (has cool) & (un-cool type) → not that expensive
 ↳ expensive, more accurate → more accurate.

plant under stress → roots look cooler.

3D imaging:

structure from motion (SFM): used in UAV imaging.

TOF (Time of flight) & Light Detection & Ranging (LiDAR)
measures time difference for making tree classification (tree, plant)

UAV imaging:

phenomenes → cars with sensors.

unmanned aerial vehicles → drones.

manned aerial vehicles → small planes.

the higher the resolution, lower the image quality.

satellite has low resolution images. 10m per pixel.

drones " high " " " " " "

Reason for using drones. UAVs

① independent data acquisition.

multi-rotor, fixed wings are used in drones.

↳ field estimation.

↳ weed detection

↳ disease detection

↳ biomass estimation.

↳ plant height measurement.

UAV based sensors at NMBU:

multi-spectral

↳ microwave Red Edge - M (Best) [old]

↳ phantom 4 multi-spectral (easy & accurate to handle) [new]

Photogrammetry:

from 3D to 2D

from 2D to 3D

↳ uses photogrammetry for doing

Auto-mosaic is always not that good.

Examples from field phenotyping at NMBU. (Bioscience,
Robot
image)

⇒ NDVI maps based on drone images.

⇒ Deep learning for image analysis.

Remote sensing

Active → no need of external light source.

→ no shadow in the data.

LIDAR (monochromatic) → Light detection & ranging

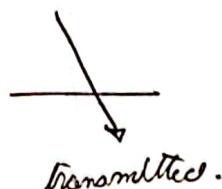
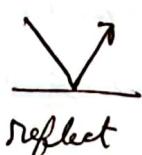
measures laser beams when it hits a target.

Passive → need light source. multi-/hyper-spectral sensor.

→ need sun. (High-spectral image)

Camera → passive → need daylight.

flash → to camera's active sensor



0.4 - 0.6: chlorophyll.

1 - 2.4: → water.

white has more reflectance than black.

5-8: multi-spectral; 8 less wavelengths. ^{less bands} 5800. have sharp edges.

Hyper-spectral: nearly continuous info. 400 - 2000 + bands
more smoother, more bands.

51%:

color important for classification.

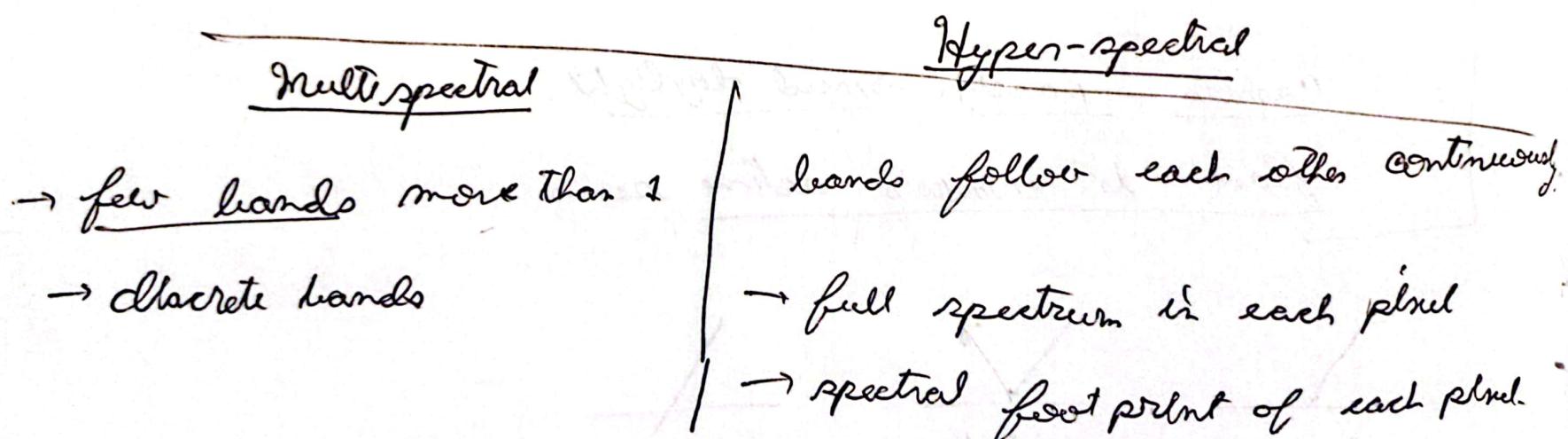
high-spectral → analyze texture.

texture - gray image -> calculate σ^2 .

Feature of hyper-spectral & LiDAR:

shadow is always detected as pen 1.

$$NDVI = \frac{NIR - RED}{NIR + RED} \rightarrow \text{will detect the vegetation.}$$



(1)

(2)

L11

Last class

22.11.2022

2020

Next week no lesson

Task 1: python & fiji both fine.

explain what you are doing.

You can also choose laplace

VSM \rightarrow $I_{smooth} \rightarrow I^*$ gauss

$$I_{vsm} = I + \alpha(I - I_{smooth})$$

write code,

if you are unable
to do \rightarrow write
pseudo code.

Image 1

(1) convert to 8 bit

(2) Filters \rightarrow unsharp
mask

\rightarrow choose sigma.

$$\alpha = 7$$

white car with observations with
different values used.

Task 2: thermal camera used to detect fault in
solar panels.

Image 2

(1) 8 bit

(2) split channel

(3) blue \rightarrow easier to threshold

(Best)

Image - LAB stack

\hookrightarrow more good enough

Illustrate what kind of
operations you can do.

- green \rightarrow red (might work)

keep lines []
" " " "] for both images.

[you are allowed to crop image
for removing unnecessary parts]

[make the histogram & say its not a good idea.]

= local vs. sun → thresholds a lot of noise.

= global vs. sun → works better.

Tank 3 UV fluorescence

In dark, use a UV torch to take photos.

[fluorescent present in the panels will react with the UV torch and show.]

[Oxygen will come out of the cracks and destroy fluorescent → to find cracks.]

Image 7:

process color - split channel → believe (best). → not all different
process image - type - lab stack - LAB (L image best)

→ stack to images → take L image.

↳ make 8 bit → or

↳ enhance contrast.

Crop rules ion
" " "] for both images.

You are allowed to crop images
→ for removing unnecessary parts

make the histogram & say its not a good idea.

= local otsu → thresholds a lot of noise

= global otsu → works better.

Tank 3 UV fluorescence

In dark, use a UV torch to take photos.

[fluorophores present in the panels will react with the UV torch and show.

[Oxygen will come out of the cracks and destroy fluorophores → to find cracks.

Image 7:

process color - split channel → blue (best). → no other different

process image - type - lab stack - LAB (L image 1st is best)

→ stack to images → take L image.

↳ make 8 bit → or

↳ enhance contrast.

pros: take blue. (Better than L)

image → auto-threshold → try all

→ try others (cracks are seen)

black parts → dark no UV lights.

[***]

EXAM start Monday 5th
deadline Sunday 11th

- describe what you try
- what you have done
- write your understanding

Say you have old operator in image 7 and choose this image and did rest of the code on the selected image.

- histogram
- then cumulative hist. (not ideal equalized histogram)



→ after stretching → again → histogram.

when thresholds → both local and global threshold.

local → not a good idea.

thresholds all the noisy part.

global →

cracks (if not etc)

→ very low signal

→ will amplify the noise.

Task - 4

Read numpy file →

[you can crop unnecessary part
↳ if it is too big for your PC.

RGB image

~~R G B~~ → order for the image

In class lecture wrong.

blue $(400 \rightarrow 450)$ peak 450

green → peak 550

red → peak 650

→ take the corresponding band → in file it says
from hand 1.

water is black

color panel blue

veg → green & yellow

Better than 2 hand.

more accurate compare to ① hand.

more hands → average

Range of bands 10: 20 → mean along axis 9
40: 50

1 hand →

Spectrum image → explain the image.

as flat → because about all other the area grass.

put legends and axis MUST
title



→ take mean along X and Y axis. (axis = 0)

20 pixels → mean spectrum: → area of 20 × 20

mean spectrum

it will make the graph much smoother (spectrum)

→ easier to see and understand

NDVI → manual & function both allowed.

the old both.

v_{min} , v_{max} → adjust for better view.

0 0.7 (1 - 4 7.21 π = 7π)

if → atmospheric correction for $\pi \approx 2\pi$

Greener → the better.

dark green → lot of chlorophyll.

$\pi \approx 2\pi$ → not healthy → less green.

misclassification. → $\pi \approx 2\pi$ → $\pi \approx 1$

⑤ PCA score

score images \rightarrow PCA images

Check if there is at least 3 component.

$$0, 1, 2 \rightarrow 3 \text{ tr}$$

0.99 - 9 55 PC 0%

0.999 - 9 161 PC 2%

0.95 - 9 161 PC 1% R(?)

↓ or lower.

adjust v_{min} & v_{max}

PC3 \rightarrow solar panels and some vegetation.

PC3 \rightarrow only vegetation, no solar panel.

Can look at PC3 or PC4 \rightarrow for understand.

PC3 \rightarrow very noisy (not much informative)

loadings

loading? PC2 \rightarrow (solar panel)

pcas

for score image?

wavelengths are variables
pixels of PC-score sample.

solar panels very high value. so might be in
the range of (0-75) or ().

Task 2 K-means → from PC component OR
from whole image. (might be too noisy)
→ might have better result on reduced.

can do both and see differences.

does not work good, not optimal.

↳ check → headings from K-means.

improve graph it!

Task 3: # do gaussian classification.

the rest

337 449

349 433

311 7

214 12

ground truths.

green → dark solar panel.

red → vegetation.

pink → dark road in front of solar panel.

dark tree		grass		asphalt		dark roof	
249	910	280	258	80	148	97	284
272	329	293	282	90	169	106	303
254	312	155	230	154	226	92	29
281	317	162	239	166	233	103	30

orange roof

dark tree

253	313
269	318
326	

254	310
265	310

roof house

160	232
166	239

309	129
315	133

dark road

291	190
289	206

290	275	85	150
310	295	105	170

95	300
110	220

low signal in image \rightarrow contrast diff.

noise amplify 2^{12} dB

spectral foot prints / are same \rightarrow different curves in loadings plots.

Q1 spectra \rightarrow Y-axis = ?

Q2 PCA \rightarrow percentage = ??

first take required PCAs = ?

team: platform

loading plot = ? explanation = ??

which band no you get a good wavelength.

rubber object

PCA2 \rightarrow vegetation

black back ground

which band contributes to most variance = ?

L-1

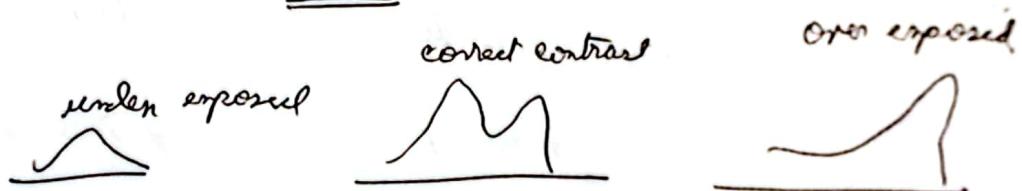
human can discriminate brightnes change
more → intensity change

contrast: same intensity → but color layer R G B
different R G B, contrast helps in identify

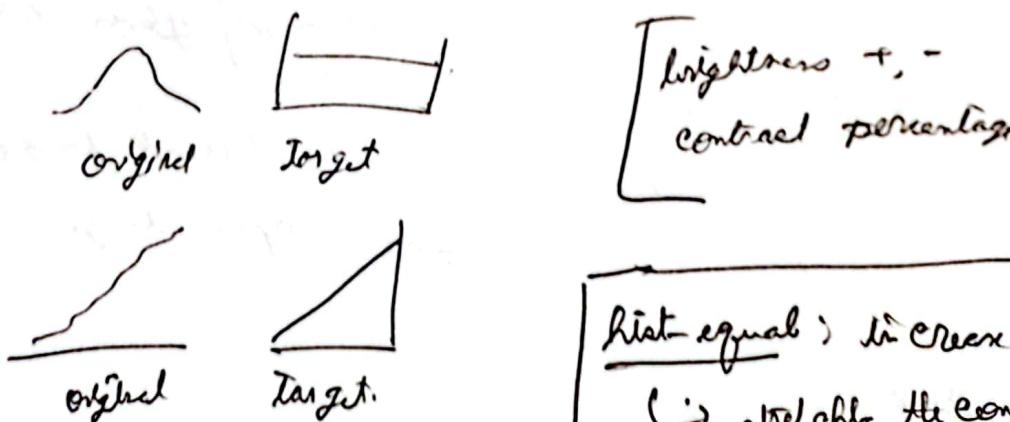
pixel value: gray | $\frac{R G B}{R = 0-255, G = 0-255, B = 0-255}$

Humans separate R-G letters than Blue-Yellow
Red-Green

L-2



Hist-equalization → histo with increasing contrast



brightness +, -
contrast percentage

Hist-equal → increase contrast

↳ stretches the contrast

↳ skewness →

flat or bumpy → ↑ here

- ① thresholding → as a point operator
② inversion →

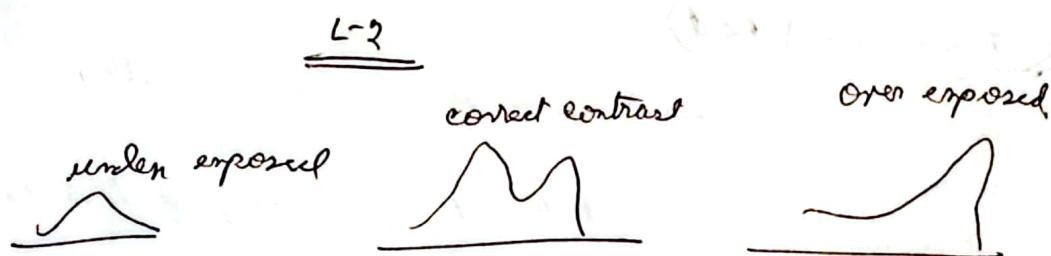
L-1

human can discriminate brightness change
more → intensity change

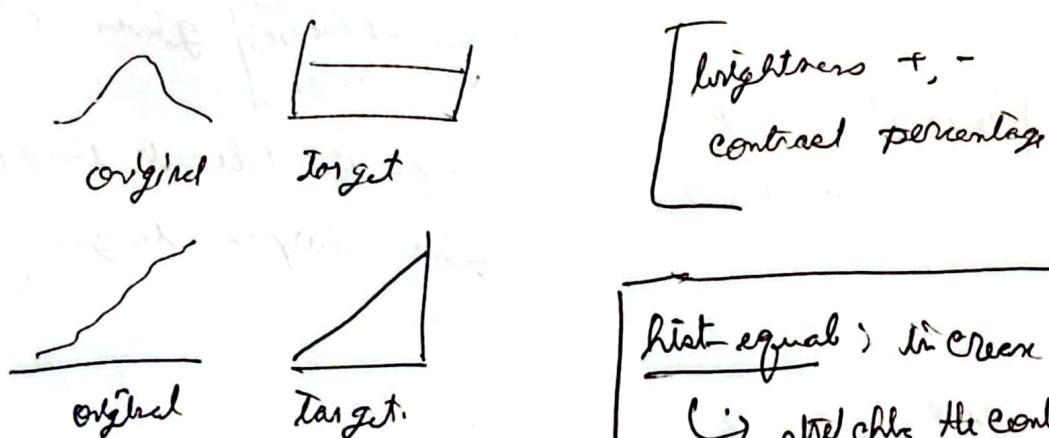
Contrast: same intensity → but outer layer vs. others
different mtn. contrast helps us identify

pixel value: gray | $\frac{R+G+B}{3}$
 \downarrow $0-255$ | $\frac{0-255}{R}$, $\frac{0-255}{G}$, $\frac{0-255}{B}$

Humans separate R-G letters than Blue-Yellow
Red-Green



hist-equalization → helps with increasing contrast



hist-equal → increase contrast
↳ stretches the contrast
↳ skewers →
Hist of library → 2 bars

- ① thresholding → as a point operation
② inversion →

Local Filters

Filters / point operation

→ works on 1 pixel.

works on multiple pixels.

→ to blur & sharpen → need filter

local blurring / smoothing filters:

① mean filter → takes the mean from range.

non-linear, ② max filter → takes the max from range. (white \rightarrow black)

③ median filter → sorts and takes the mid one.

non-linear, ④ minimum filter → takes the min from range (black \rightarrow white)

problem of linear filters → smoothes edges, & lines.

Reduces image quality.

⑤ Gaussian: (Best)

Compared to linear \rightarrow non-linear filters better.

[non-local-means → better at preserving of textures]

(\hookrightarrow) denoise-nz-means

just mean \rightarrow is not local.

Convolve = ?

[residual = original - $\begin{cases} \text{denoised image} \\ \text{filtered image} \end{cases}$] gives edges.

local \rightarrow denoising filter \rightarrow on the blurred image gives sharpen image.

blur

~~*~~ Denoising filters

original - denoised = edges

Best \rightarrow Gaussian \rightarrow sigma vs vs blur.

~~3rd~~ ① median [preserves edges while smoothes]
② mean

2nd best ④ non-local.

median \rightarrow sharper? removes noise
that's why looks sharper

non-local \rightarrow uses mean filter



L-4 (edge) \rightarrow Gaussian ones are best
& Contours

edge \rightarrow when image positions where the local intensity vary dramatically in relation to its surroundings.

edge
① Prewitt filter \rightarrow 1 in the center. line & col.
and work

$$H_x^P = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 1 \end{bmatrix} \quad H_y^P = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 6 \\ 1 \end{bmatrix}$$

edge
② Sobel filter \rightarrow higher weight to center line & columns than prewitt.

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

edge
③ Canny filter: (multi-stage edge detector) : uses Gaussian.

- \rightarrow sigma of gaussian smoothing
- \rightarrow hysteresis thresholding (min & max)

low sigma \rightarrow edges with lot of noise.

high sigma \rightarrow least the perfect edge.

L-4 (edge) \rightarrow Gaussian ones are best
& Contours

edge \rightarrow ~~when~~ image positions where the local intensity vary dramatically in relation to its surroundings.

edge
① Prewitt filter \rightarrow 1 in the center. line & col.

$$H_x^P = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 1 \end{bmatrix} \quad H_y^P = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

edge
② Sobel filter \rightarrow higher weight to center line & columns than pre-wit.

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

edge
③ Canny filter: (multi-stage edge detector) : uses Gaussian.

- \rightarrow sigma of gaussian smoothing
- \rightarrow hysteresis thresholding (min & max)

low sigma \rightarrow edges with lot of noise.

high sigma \rightarrow lost the perfect edge.

~~worst~~
edge used for sharpening

④ Laplace filter: uses $f''(x) \rightarrow$ 2nd derivative.

~~used for sharpening~~

X ⑤ low pass filter (L) passes low frequencies, coarse structure, long wavelengths.

$$L = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

~~sharpening~~
~~2nd best~~ ⑥ High pass filter (H): passes high / fine structure / short wavelengths.
→ makes image sharp.

$$H = I - L$$

$$= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

~~sharpening~~
~~best~~ ⑦ Unsharp Mask (USM): sharpening using edge detectors.

sharped image \rightarrow original image + smoothed (unsharped) image.

$\alpha \rightarrow$ weight factor \rightarrow that controls sharpening.

$$\underline{\text{mask}} = M = I - (\text{smoothing, } I \times \text{unsharpness filter})$$

$$\underline{\text{sharpened image}}, I = I + \alpha M \quad \xrightarrow{\text{amount of sharpen}}$$

⑧ Laplace sharpening: does not work that good.

L-5 (morphology) → used on Binary image.
→ modify shape

Binary image - (Skeletonize)

1 → pixel in foreground (object) [white]

0 → background [black]

Morphology: ∇ / Kernel → is the area size defined by us.

↳ disk, square, diamond, etc. (ball for 3D)
↳ Range (Zone) → for the filter to work.

- ① Dilation: ∇ takes max over the kernel area
→ removes holes. (grow)
→ usually square/disk
- ② Erosion: ∇ removes small objects. (shrink)
→ makes holes huge
→ takes min over the kernel area.

~~Contours~~ : Border/ edge of the image.

~~filter~~: shrink - grow

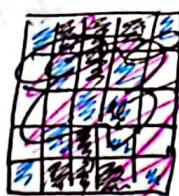
- ① Open (erosion - dilation):

→ smooths objects, removes noise.

- ② Close (Grow Shrink
dilation - erosion)

→ smooths objects, fills in small holes

~~Thinning~~ → shrinks the object, unless a pixel is left
Skeletonize: → Object should be white, background black contours



If object white → skeleton → correct

If object black → skeleton → wrong

Filters → can be used on both gray & binary image.

- ① max filter → Dilation/grow: Process → Filters → Minimum
→ takes max value of the local zone.

- ② min filters → Erosion / shrink.: Process → Filters → maximum.
 → Takes min values of local zero.

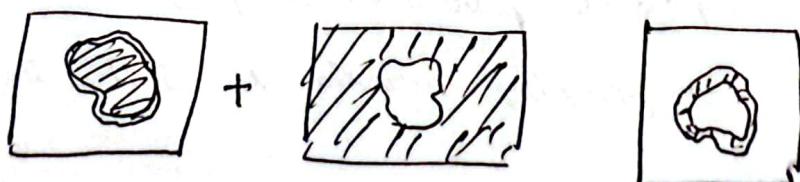
- S-20! Convert to mask?

- ③ Median filter: preserves edges while removing noise.

 - ↳ Blurs image, but preserves edges.
 - ↳ Kernel goes -> sort sort sort \rightarrow take the median in the anchor point.
 - ↳ used for smoothing heavy noise/percolated image.

Contours: object black \rightarrow dilate shrinks (1 pixel)
 \rightarrow invert the shrink. (object white small)

Original + Inverted small = contours.
(black) (white)



$$\begin{array}{l} \underline{\text{RGB}} \rightarrow R \rightarrow \\ G \rightarrow \\ B \rightarrow \end{array}$$

$$\begin{array}{l} \underline{\text{CIE LAB}} \rightarrow L \rightarrow \\ A \rightarrow \\ B \rightarrow \end{array}$$

L-8 (Texture Analysis)

Statistics on pixel values / Texture feature extraction:

type 1: 1st order statistics

- (1) Histogram → mean
mean
- problem → does not tell us anything
↳ different texture, same histogram
- solution → take patches
do small hist
→ or do GLCM

Higher order statistics type 2: GLCM: Grey level co-occurrence matrix

plot & see → the texture classification.

→ pattern

→ counts patterns or ~~group~~ of re-occurring pixel pairs

→ grouping according to similar texture

L-11 (Spectral Imaging)

(Visible light)

HUMAN VISION: 400 - 700 nm

~~RED: 410 - 490
GREEN: 510 - 680
BLUE: 420 - 490~~

Hyper-spectral camera:

ultra violet: 200 - 400 nm

visible light: 400 - 700 nm

Near Infrared: 700 - 1300 nm.

Hyper-spectral data: gives a detailed spectrum of channels in the ^① visible and ^② near infrared and ^③ shortwave infrared., bringing out the invisible differences in the surface material.

Human Vision/Visible light: 400 - 700 nm

RED: 650 - 70 nm [Approx: 645 nm]

GREEN: 490 - 595 nm [Approx: 510 nm]

BLUE: 420 - 490 nm [Approx: 440 nm]

Classification: Assigned pre-defined labels to objects based on their features.

Clustering: no of clusters will be told. Grouped according to their similarity present.

Classification

① Supervised → uses where the sample pixels are images.

→ Gaussian maximum likelihood classification (GMLC)

② Unsupervised → grouping based on common characteristics without labeling any sample.

→ K-means.

PCA in score images : black → background
color → other objects visible
in that PCA

look at loadings I score & and they there's peak or
high low because these things are visible on the
score image.

repetition reflect in green.
Green 490: 575: → small bump in this point, confirms
vegetation. # After Red peak to near infrared (vegetation)

all other objects: flat spectrum

black → low score

other → high score

specific "shape" of vegetation: [red low for vegetation,
NIR high " "

Classification

① Supervised → user chose the sample pixels in images.

→ Gaussian maximum likelihood classification (GMLC)

② Unsupervised → grouping based on common characteristics without using any sample.

→ K-means.

PCA in people images: black → background
color → others / objects visible
in that PCA

look at loadings I score & and they there's peak on
high here because these things are visible on the
score image.

vegetation reflect in green.
green 490: 575: → small bump in this point, confirms
vegetation. # After Red peak to near infrared (vegetation)

all other objects: flat spectrum

black → low score

others → high score

specific slope of vegetation:

red low for vegetation.
NIR high. "

~~Score image~~

Light \rightarrow High score
dark \rightarrow low score.] Opposite from each other in PC scale.

loadings corresponds to wavelengths. By loadings, we can see which wavelength have been given the weight to generate score image.

PCO \rightarrow flipped from vegetation. Instead of peak at green, fall at green.

negative value

spectral signature

Cannot say directly which PCA it is.

\rightarrow intensity (arbitrary unit)

PC1 \rightarrow vegetation low at red high at NIR

PCO \rightarrow opposite of vegetation. (vegetation is black)

score color image

<u>grass</u>	<u>asphalt</u>	<u>black roof</u>	<u>red roof</u>
402 40	253 769	719 735	133 886
422 76	268 791	742 770	150 894

<u>solar</u>	<u>water</u>
405 429	713 896
411 439	751 994

circle

<u>grass</u>	<u>white roof</u>	<u>soil ground</u>	<u>asphalt (4 way)</u>
387 11	300 330 341 366	961 641 982 702	252 772 272 794
432 61	379 530 395 625		

<u>black</u> <u>dark roof</u>	<u>road - tarmac</u> <u>concrete ground</u>	<u>tree</u>
258 520	316 232	122 71
283 553	347 287	157 117

<u>green roof</u>	<u>red roof top</u>
296 656	133 863 149 882
324 685	127 620 136 636

* *
alpha = 40
nd image
- lens
alpha =
sharpened = blurred
+ alpha * (blurred f -
focal blur)

155 439

mult - convolve

2732 3643

Tack 1:

2/3 → convert



① mult - convolve. (cont)

② median filter

keeps the edges okay.

- ① Laplace
- ③ USM
- ③ High

sigma
rob
amount.

try

median on RGB
* on gray
too

Tack 2: a) should it be on the RGB or
the gray image (Ingen)

LAB



A

a) L* → does not have shadow (gray image)



$$\frac{\text{dilate} \rightarrow 10 \rightarrow 1}{\text{erode} \rightarrow 8 \rightarrow 1} \quad \text{it counts.}$$

Default

1
1

mask

black balls

87

white background

7

94

take image
 $\xrightarrow{\quad}$
 crop
 $\xrightarrow{\quad}$
 LAB \rightarrow choose A (without shadow) } Q2
 2nd image

✓ threshold \rightarrow Li

~~X~~ lot of holes/ dots.
 \hookrightarrow dilate \rightarrow it(10) \rightarrow count 1
 \hookrightarrow erode \rightarrow it(8) \rightarrow count 1 [rest of holes]
 few remains

Closing \rightarrow 8 iter
 2(c)
 fill holes
 watershed
 Inv

V3 \rightarrow works without shadow