Robot Vision

Fundamentals and applications of computer vision

Teaching Assistant:
Marcello Calisti, PhD
marcello.calisti@santannapisa.it

Sant'Anna
Scuola Universitaria Superiore Pisa

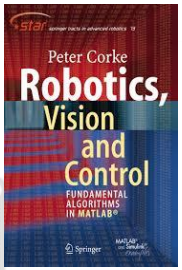
Reference materials and credits

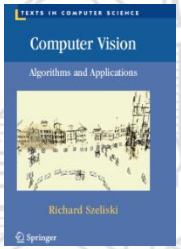
Most of the material presented in these lessons can be find on the brilliant, seminal books on robotics and image analysis reported hereafter:

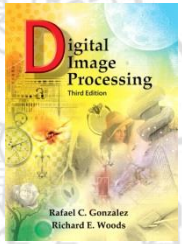
1. P.I. Corke, “Robotics, Vision & Control”, Springer 2011, ISBN 978-3-642-20143-1

2. R. Szeliski, “Computer Vision: Algorithms and Applications”, Springer-Verlag New York, 2010

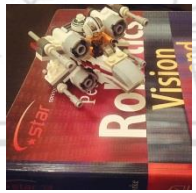
3. R.C. Gonzalez & R.E. Woods, “Digital Image Processing (3rd edition)”, Prentice-Hall, 2006



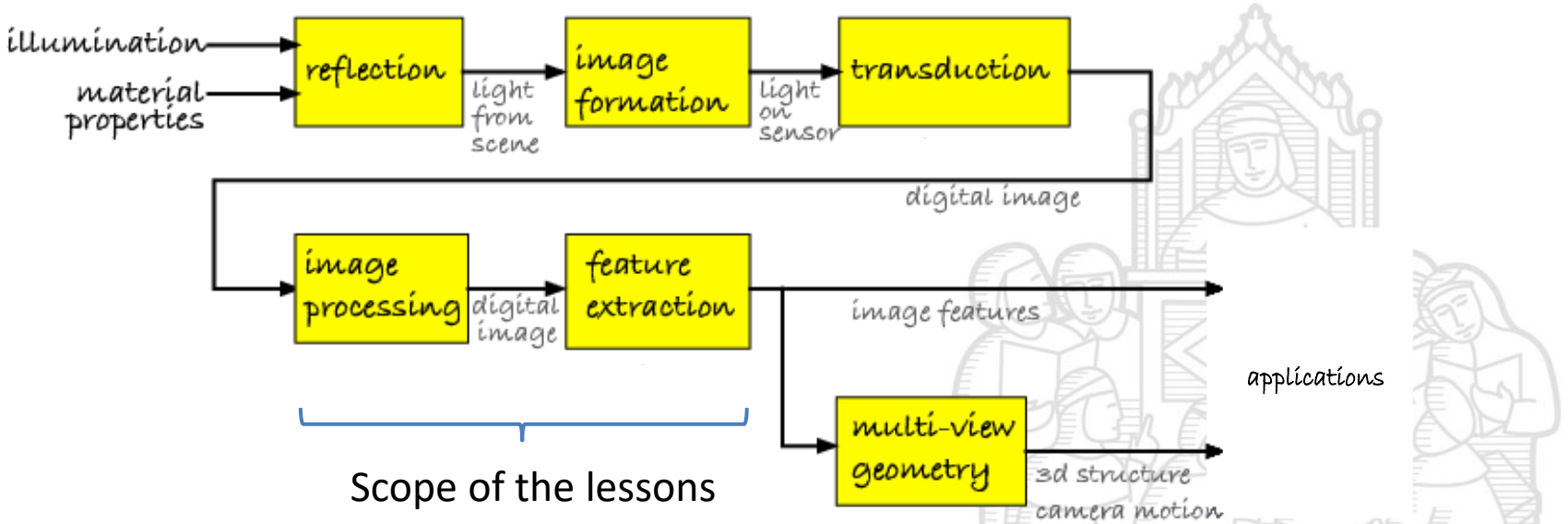




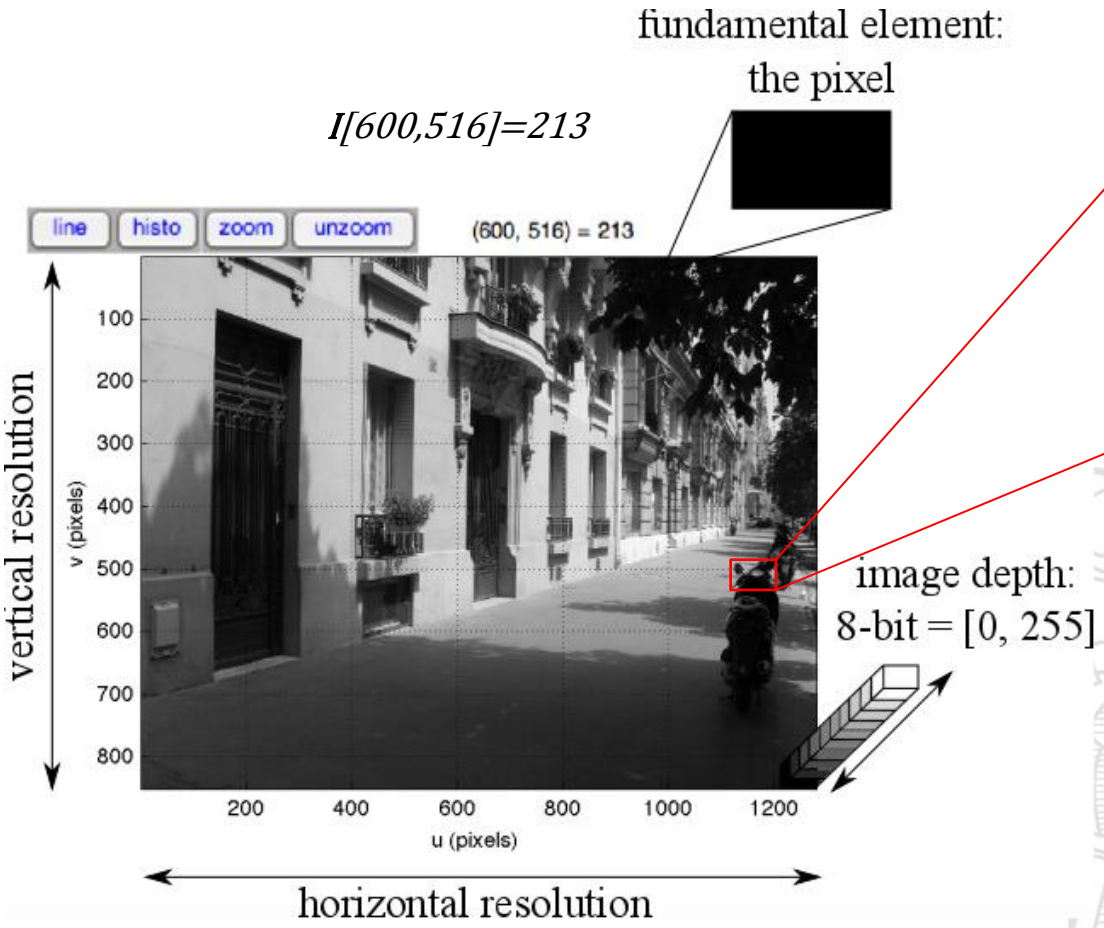
Most of the images of these lessons are downloaded from RVC website http://www.petercorke.com/RVC/index.php and, despite they are free to use, they belong to the author of the book.



Overall computer vision process and scope of the lessons



What's a digital image?



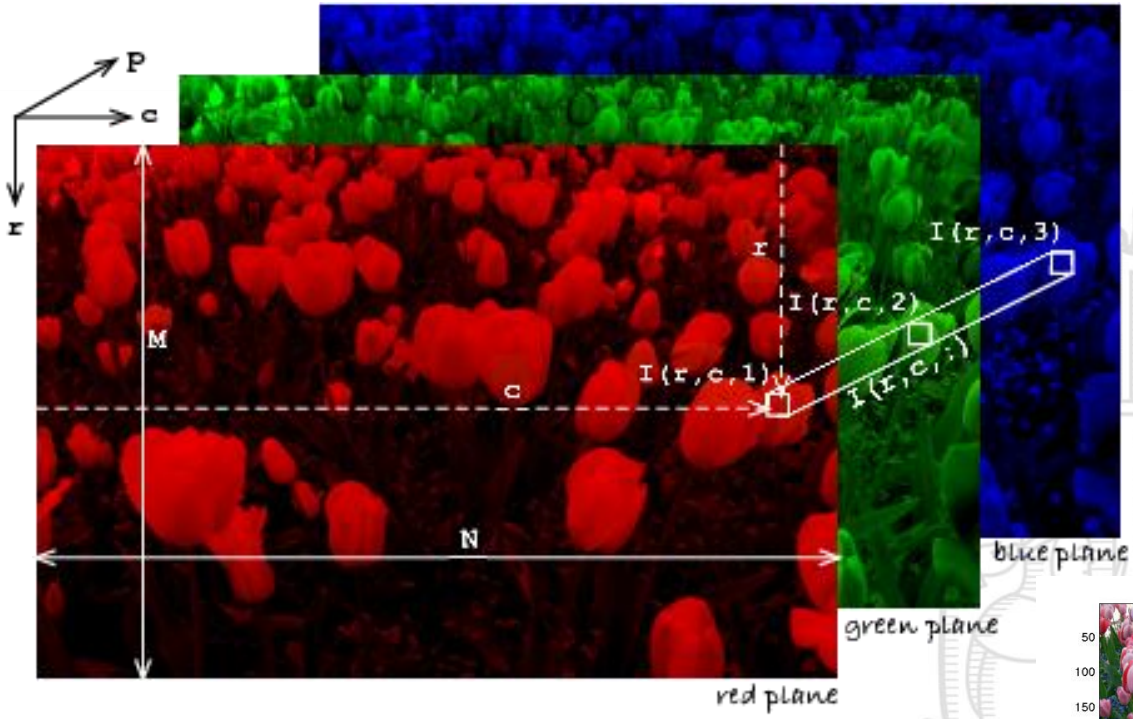
Digital images are **mosaics** made of **pixels**

Image resolution is the number of pieces (pixel) used to build the mosaic (image)

Image depth is the number of colours (levels) of mosaic pieces

Colour images

Colour images have three channels: the most common triplet is the R-G-B

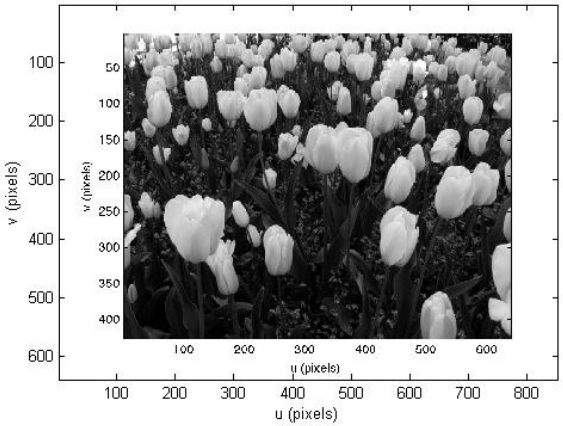


There are other very useful common space:
HSV, XYZ, CIE, YUY, …

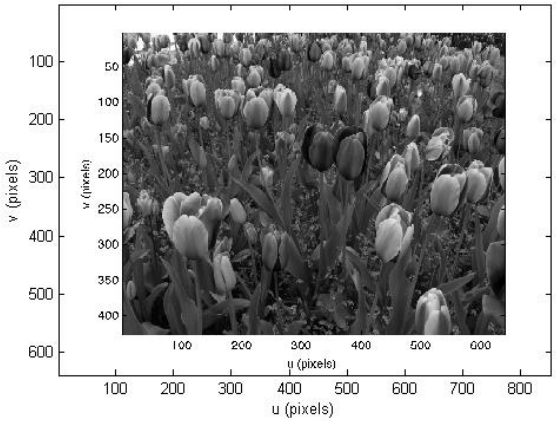
Colour images

640x854x3 uint8

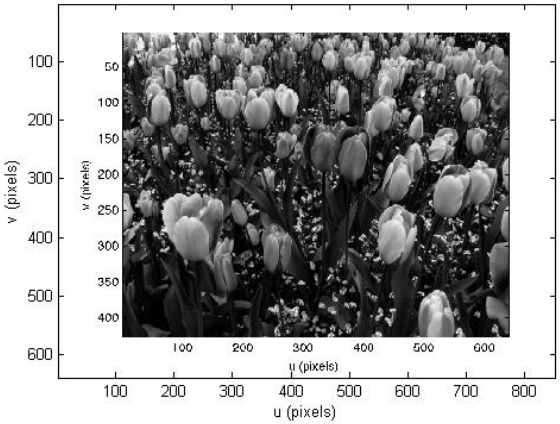
Red channel



Green channel



Blue channel

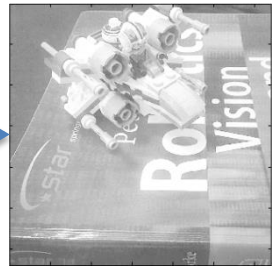


640x854x1 uint8

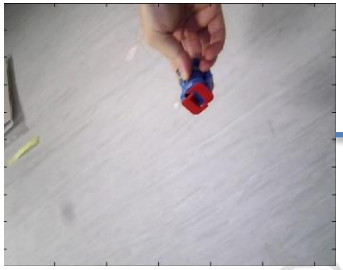
Image processing

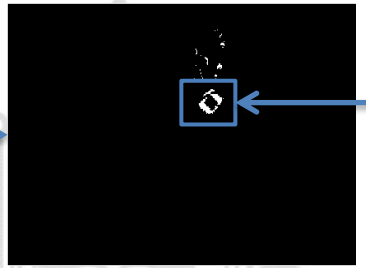
Transform one or more input images into an output image.

To enhance the image

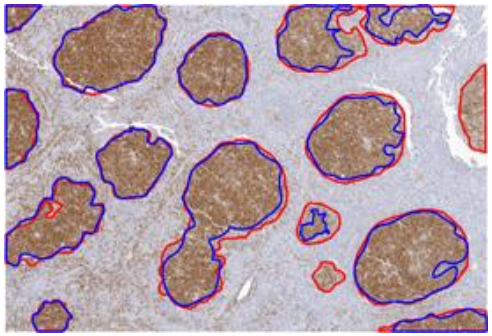


Human interpretation





Features extraction

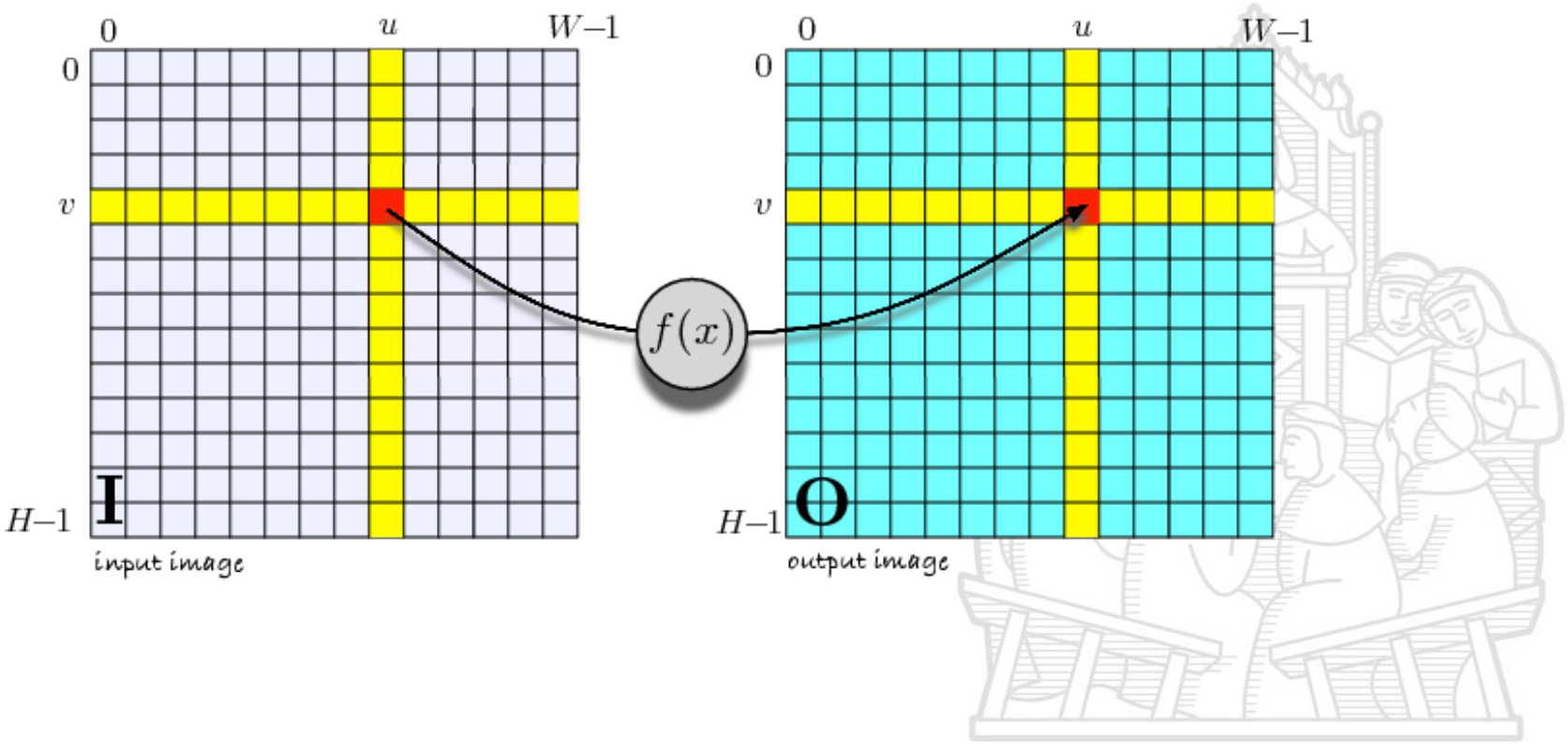


Computer aided diagnosis
Metin Gurcan, Ph.D – Ohio State

Objects recogniton
HERB robot butler – Carnegie Mellon

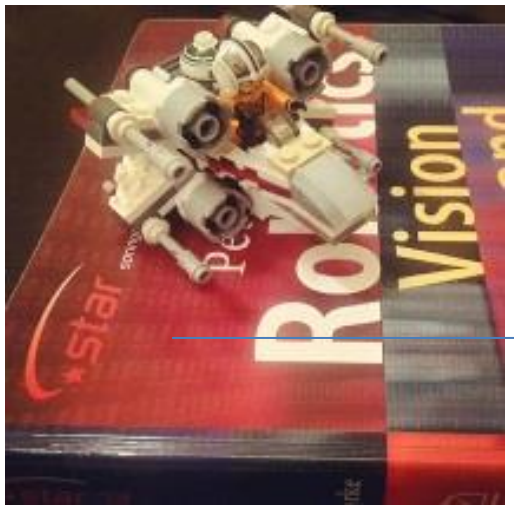
Monadic operations (pixel operators)

$$\boldsymbol{O}[u,v] = f(\boldsymbol{I}[u,v]), \qquad \forall (u,v) \in \boldsymbol{I}$$



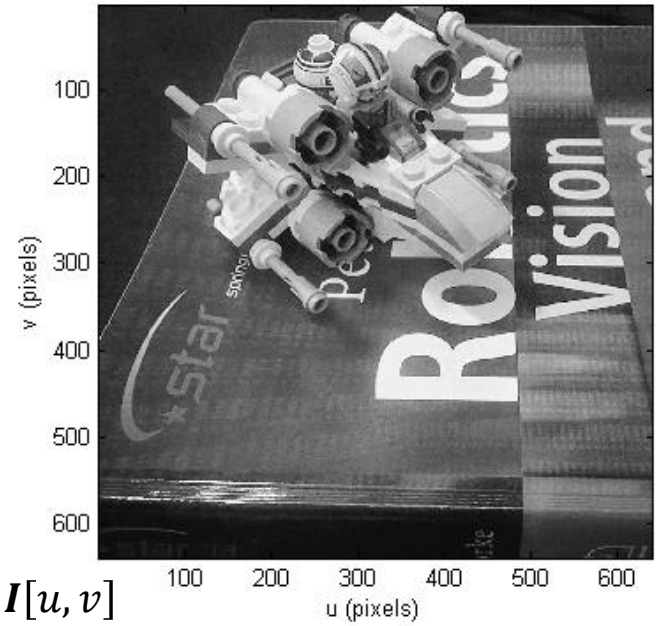
Simple monadic operation:

Gray-scale conversion with International Telecommunication Unit (ITU) recommendation 709

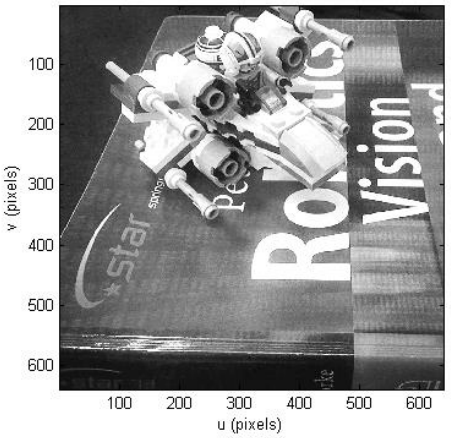


$Y=0,212R+0,7152G+0,0722B$

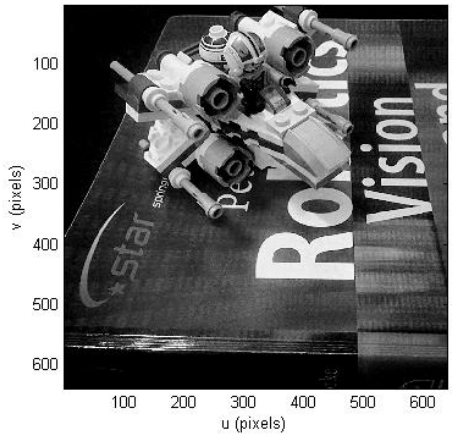
Lightening and darkening



$\boldsymbol{I}[u, v]$



$\boldsymbol{O}[u, v] = \boldsymbol{I}[u, v] + 50$

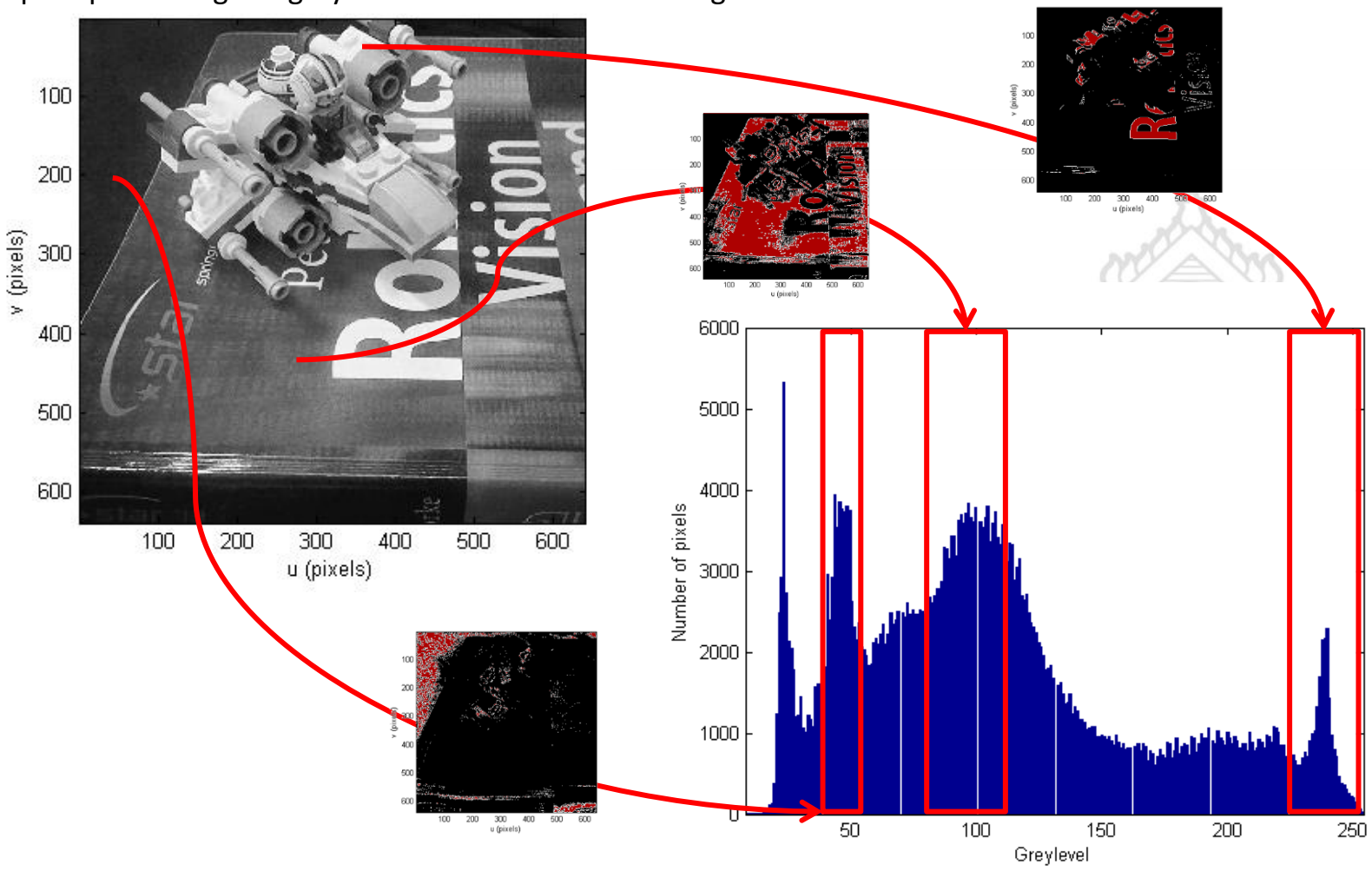


$\boldsymbol{O}[u, v] = \boldsymbol{I}[u, v] - 50$

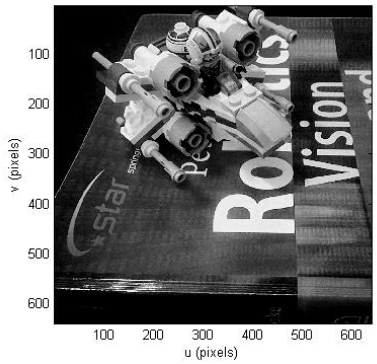
Monadic operations change the distribution of grey levels on images

Histogram

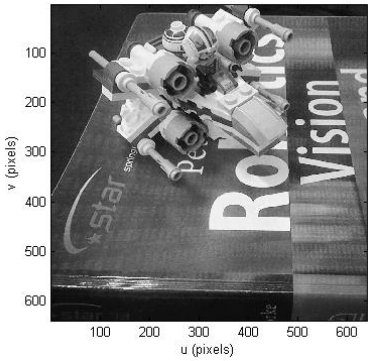
Is a graph representing the grey level occurrences of an image.



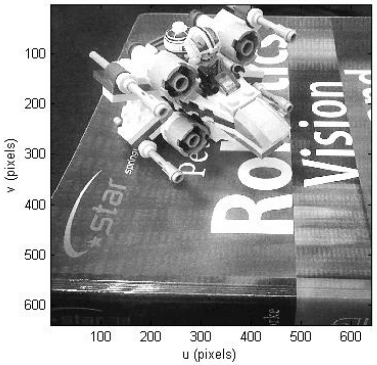
Histograms and monadic operations



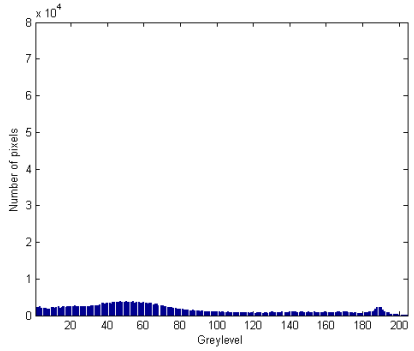
$\boldsymbol{O}[u,v] = \boldsymbol{I}[u,v]$ - 50

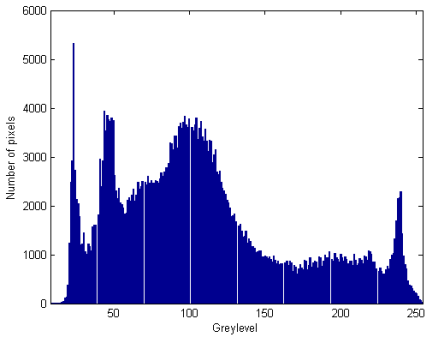


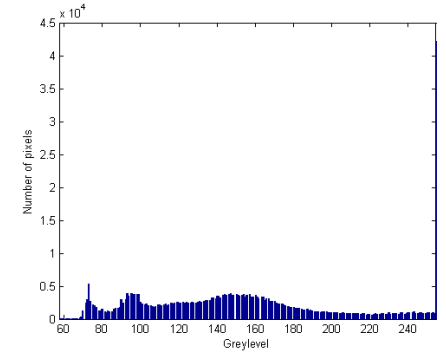
$\boldsymbol{I}[u,v]$



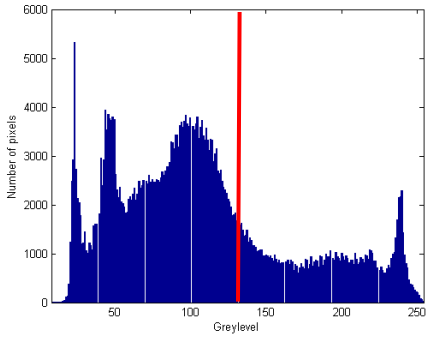
$\boldsymbol{O}[u,v] = \boldsymbol{I}[u,v]$ + 50





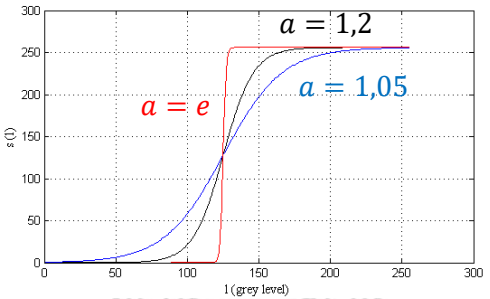


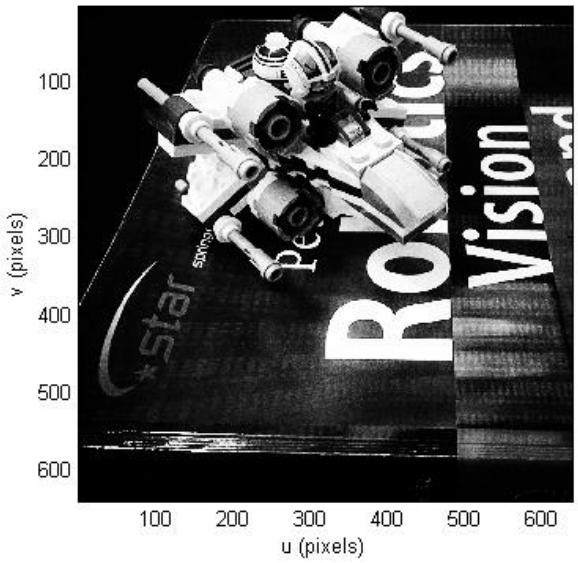
Contrast enhancement

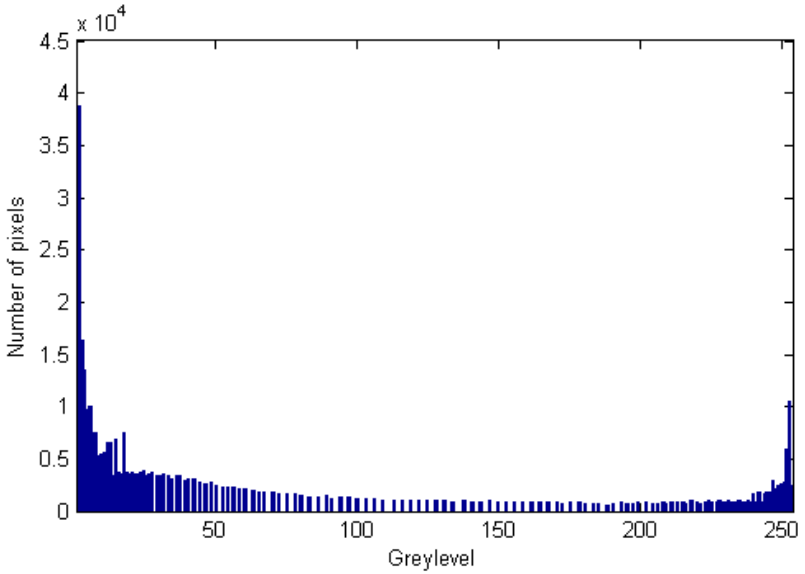


Sigmoid function

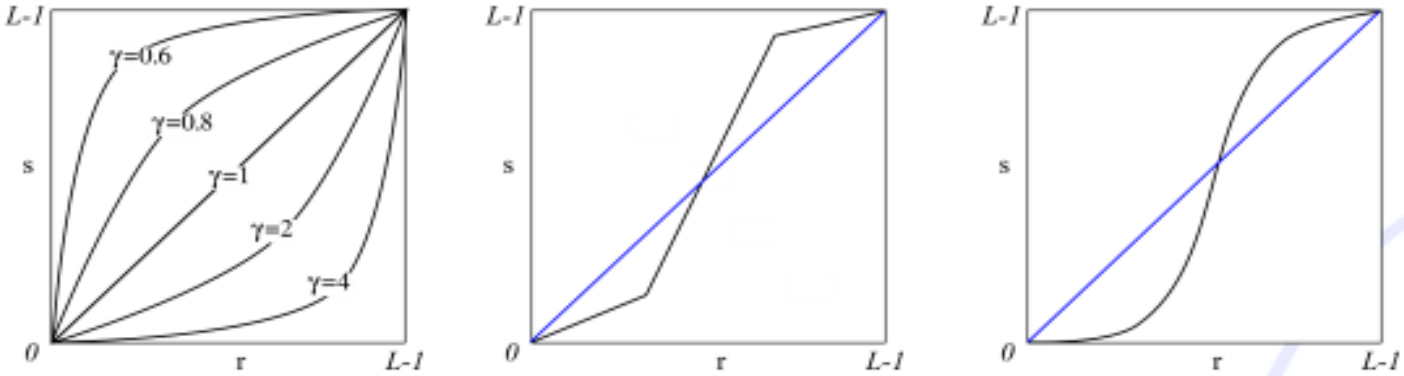
$$s(l) = \frac{256}{1 + a^{-(l-125)}}$$







Common operations



(a) Power law (b) Piecewise (c) Sigmoid

Figure: Transformations

Power law	lighten or darken
Piecewise	flexible
Sigmoid	enhance the contrast

Common operations

$$s(r) = c \cdot r^{\gamma}$$

$$s(r) = \begin{cases} c_1 \cdot r & 0 \leq r < r_{min} \\ c_2 \cdot r & r_{min} \leq r < r_{max} \\ c_3 \cdot r & r_{max} \leq r < L - 1 \end{cases}$$

$$s(r) = \frac{c_1}{1 + e^{-r}}$$

- power law
- piecewise
- sigmoid

Each function requires parameters definition

Monadic operations

Code sample >

```
% lightening/darkening
xwing_light=xwing_grey+50;
idisp(xwing_light);
xwing_dark=xwing_grey-50;
idisp(xwing_dark);
% select areas by levels
level48 = (xwing_grey>=40) & (xwing_grey<=50) ;
idisp(level48);
level225 = (xwing_grey>=225) &
(xwing_grey<=255) ;
idisp(level225);
% contrast enanch
xwing_contrast=zeros(r,c);
    for i=1:r
       for j=1:c
           xwing_contrast(i,j)=256./(1+1.05.^-(
double(xwing_grey(i,j))-150));    % Sigmoid
       end
    end
 idisp(xwing_contrast)
```

Pay attention

$$
\begin{aligned}
L &= 21 \\
c &= 1 \\
\gamma &= 2 \\
s(r) &= c \cdot r^{\gamma}
\end{aligned}
$$

$$
\begin{aligned}
s(1) &= 1 \\
s(2) &= 2^2 = 4 \\
s(3) &= 3^2 = 9 \\
s(4) &= 4^2 = 16 \\
s(5) &= 5^2 = 25 \\
\ldots &= \ldots \\
s(20) &= 20^2 = 400
\end{aligned}
$$

???

We have only 21 levels, but:

$$s(5) = 5^2 = 25$$

Pay attention

We need to remap the output between $[0, L-1]$:

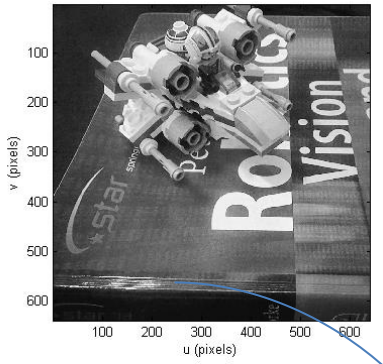
$$\frac{s'}{s} = \frac{20}{400}$$

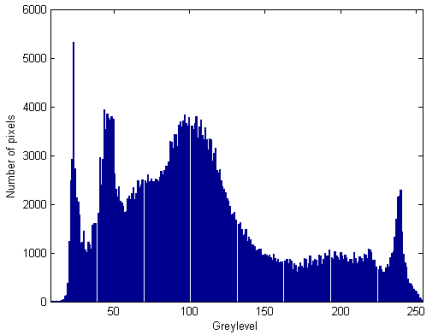
$$\frac{20}{400} = \frac{L-1}{(L-1)^{\gamma}} = (L-1)^{1-\gamma}$$

$$s' = (L-1)^{1-\gamma} s = c \cdot s = c \cdot r^{\gamma}$$

Thus c is related to L and γ.

Histogram equalization

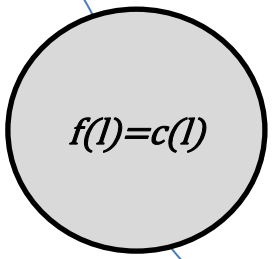




$$c(l) = \frac{1}{N}\sum_{i=0}^{l} h(l) = c(l-1) + \frac{h(l)}{N}$$

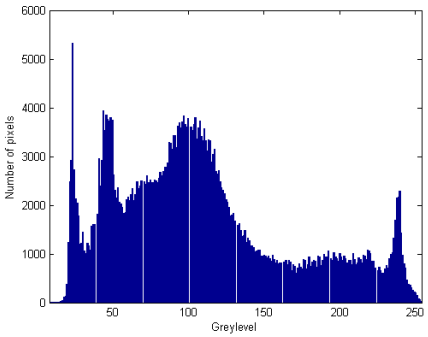
c(l)	Cumulative distribution
h(l)	histogram
l	Grey level

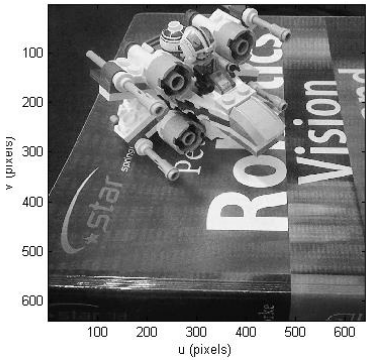
Monadic operation

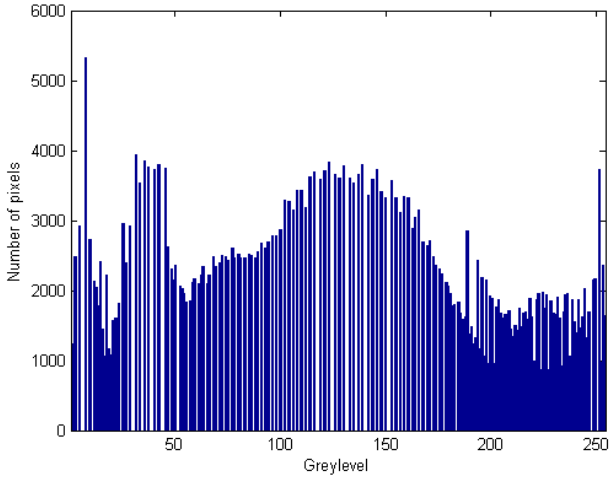


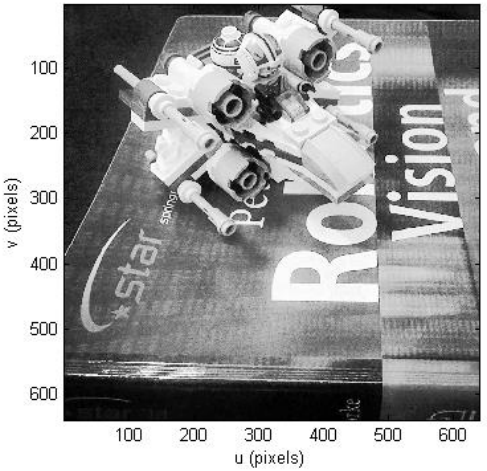
$$\boldsymbol{O}[u,v] = c(\boldsymbol{I}[u,v]), \forall (u,v) \in \boldsymbol{I}$$

Histogram equalization



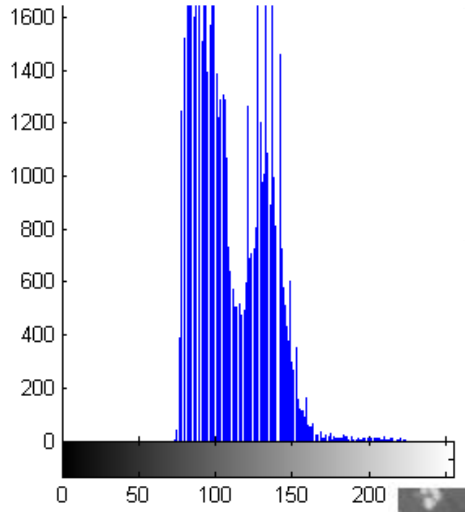






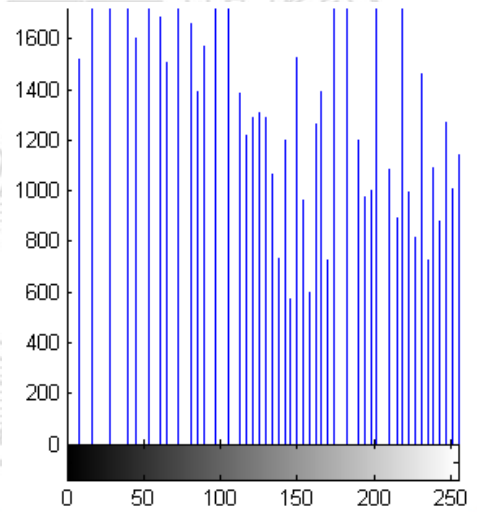
After equalization

Histogram equalization



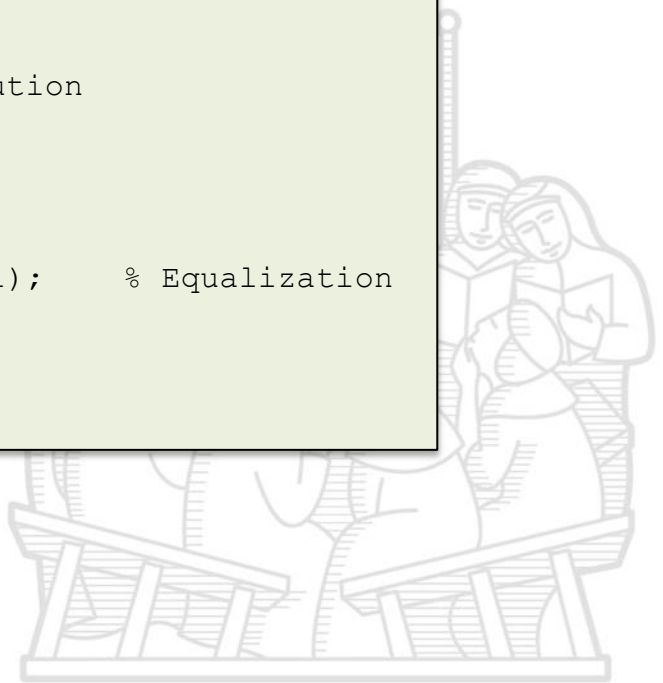
before

after



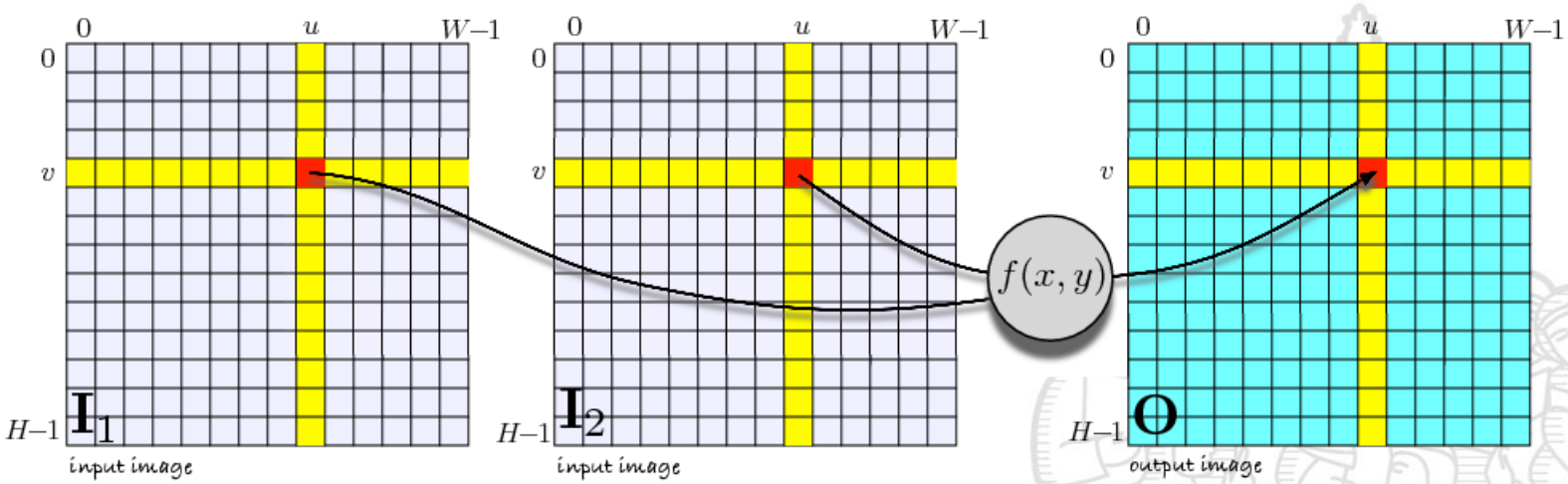
Code sample >

```
 %hist equalization
[n,v]=ihist(xwing_grey);
plot(v,n)
cd=zeros(length(v),1);
cd(1)=v(1)/(r*c);
    for l=2:length(v)
       cd(l)=cd(l-1)+1/(r*c)*n(l); % cumulative distribution
    end
xwing_equalized=zeros(r,c);
    for i=1:r
       for j=1:c
           xwing_equalized(i,j)=255*cd(xwing_grey(i,j)+1);    % Equalization
       end
    end
 idisp(xwing_equalized)
```

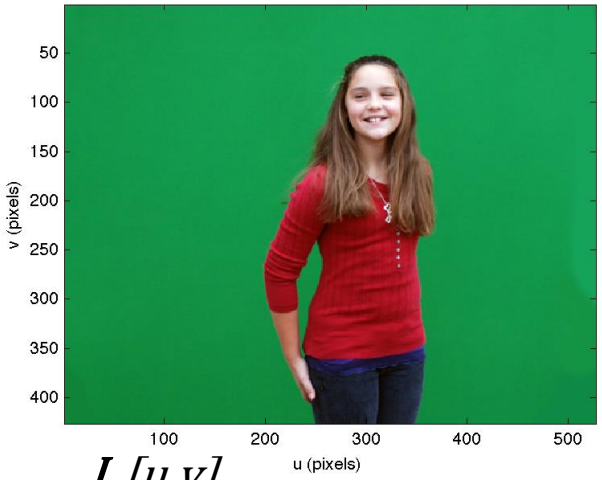


Diadic operations

$$\boldsymbol{O}[u,v] = f(\boldsymbol{I}_1[u,v], \boldsymbol{I}_2[u,v]), \qquad \forall (u,v) \in \boldsymbol{I}_1$$



Green screen



$I_1[u,v]$

$I_2[u,v]$

If $\boldsymbol{I}_1[u,v]$ isGreen

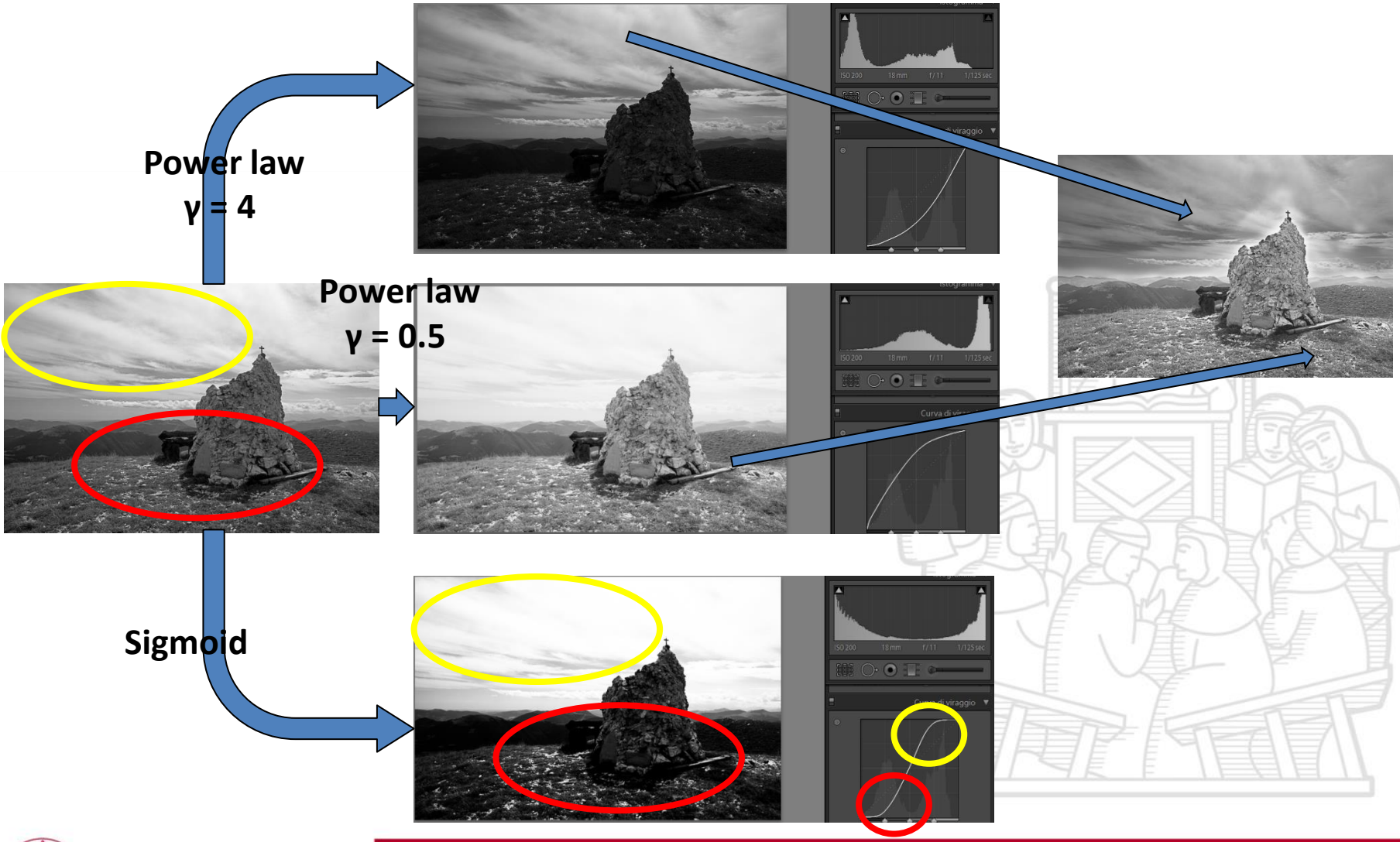
$$\boldsymbol{O}[u,v] = \boldsymbol{I}_2[u,v]$$

Else

$$\boldsymbol{O}[u,v] = \boldsymbol{I}_1[u,v]$$

$O[u,v]$

High Dynamic Range



Background subtraction

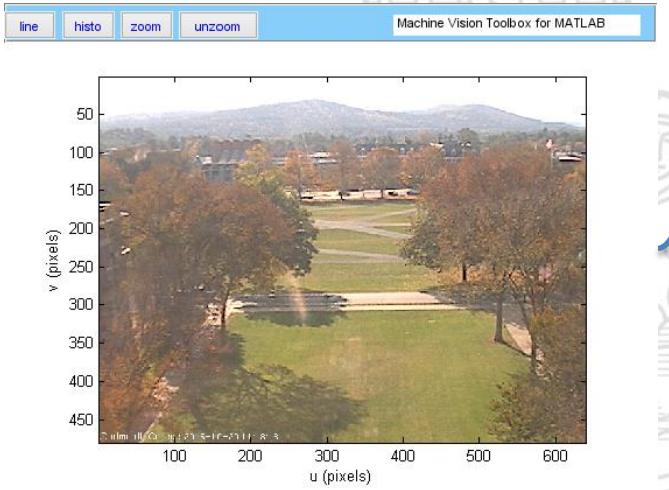
Another important diadic operation is the background subtraction to find novel elements (foreground) of a scene.

$$\boldsymbol{O}[u,v] = \boldsymbol{I}_1[u,v] - \boldsymbol{I}_2[u,v] = \boldsymbol{I}_1[u,v] - \boldsymbol{B}[u,v]$$

background

How we estimate the background $\boldsymbol{B}[u,v]$?

We can take a shoot when we know that only background is visible

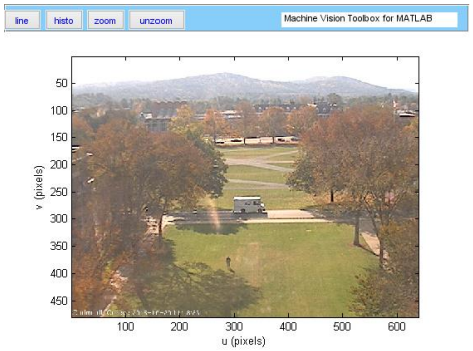


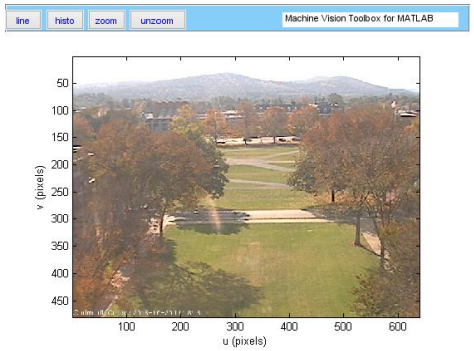
'http://wc2.dartmouth.edu', 05:19 p.m., Rome time

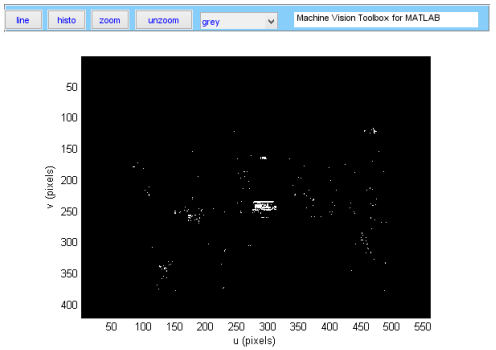
Background subtraction

'http://wc2.dartmouth.edu', 05:19 p.m., Rome time

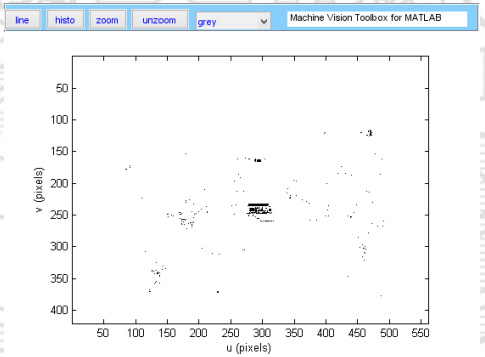
$$\boldsymbol{I}_1[u,v] - \boldsymbol{B}[u,v] = \boldsymbol{O}[u,v]$$







foreground

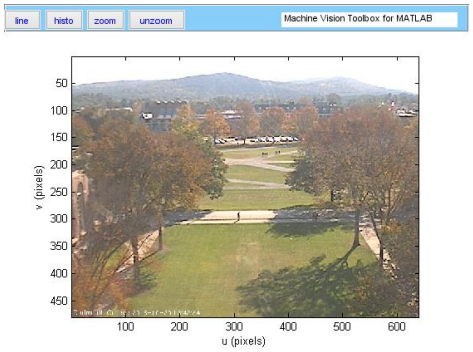


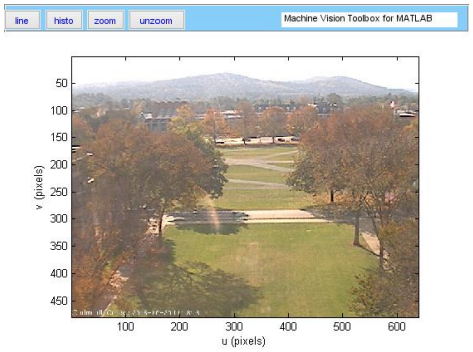
background

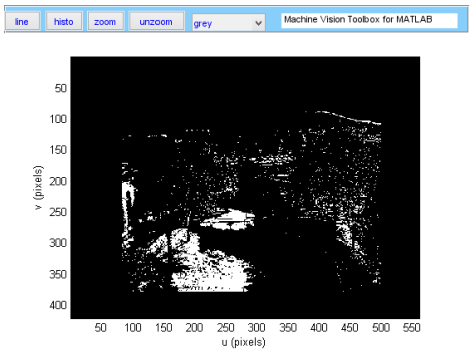
Background subtraction

'http://wc2.dartmouth.edu', 07:48 p.m., Rome time

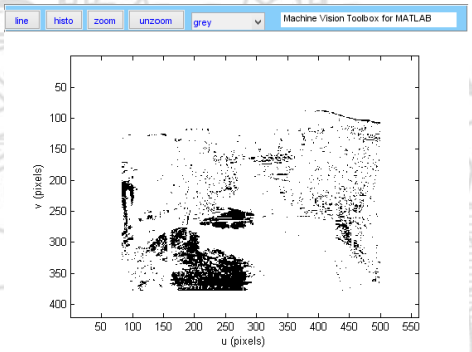
$$\boldsymbol{I}_1[u,v] - \boldsymbol{B}[u,v] = \boldsymbol{O}[u,v]$$







foreground



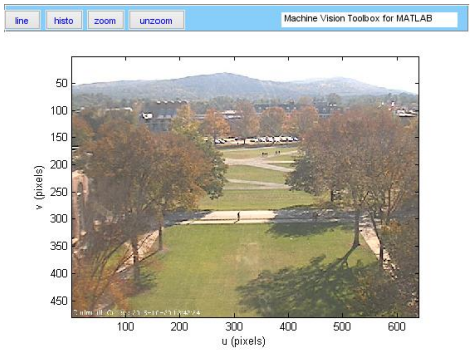
background

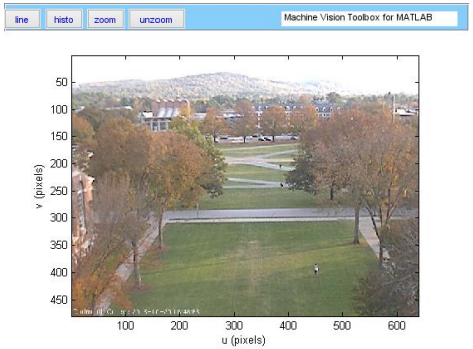
What went wrong?

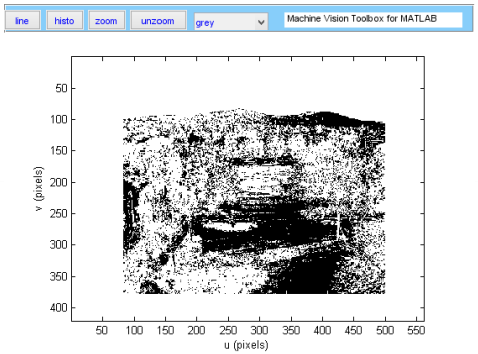
Background subtraction

'http://wc2.dartmouth.edu', 10:55 p.m., Rome time

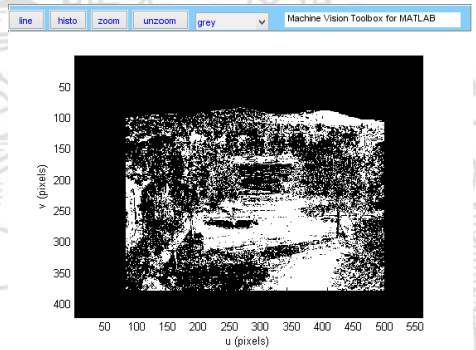
$$\boldsymbol{I}_1[u,v] - \boldsymbol{B}[u,v] = \boldsymbol{O}[u,v]$$







foreground



background

What went wrong?

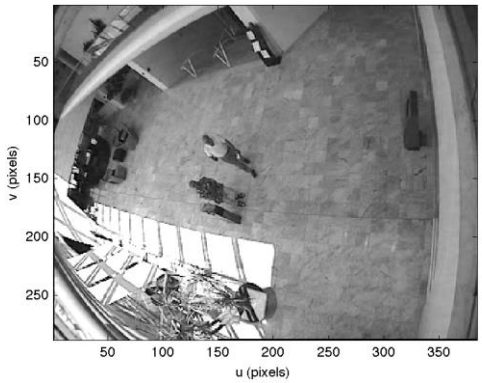
Background estimation

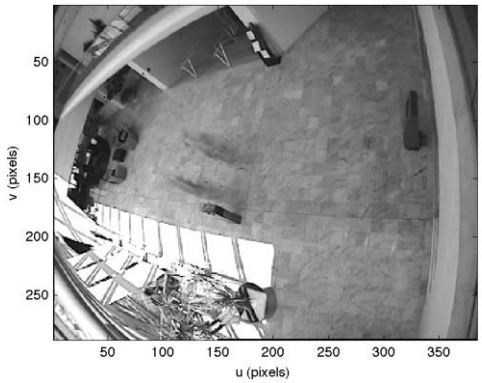
We require a progressive adaptation to small, persistent changes in the background.

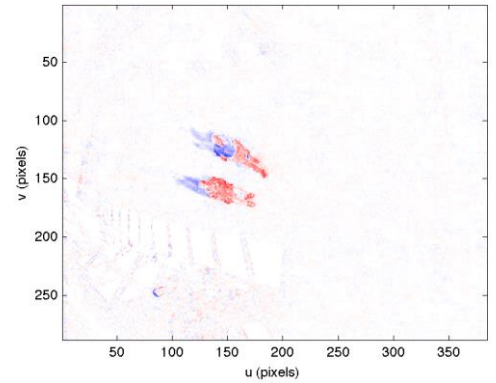
Rather than take a static image as background, we estimated it as follow:

$$\boldsymbol{B}\langle k+1\rangle = \boldsymbol{B}\langle k\rangle + c(\boldsymbol{I}\langle k\rangle - \boldsymbol{B}\langle k\rangle)$$

$$c(x) = \begin{cases} \sigma, & x > \sigma \\ x, & -\sigma \le x \le \sigma \\ -\sigma, & x < -\sigma \end{cases}$$





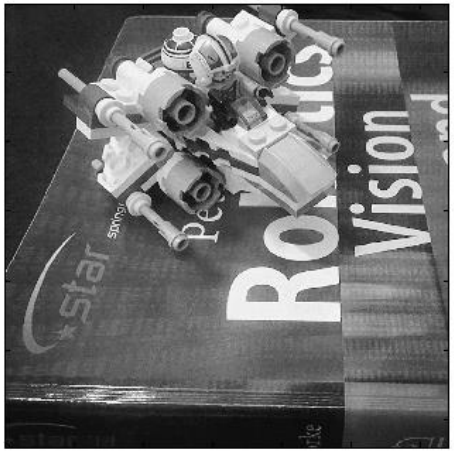


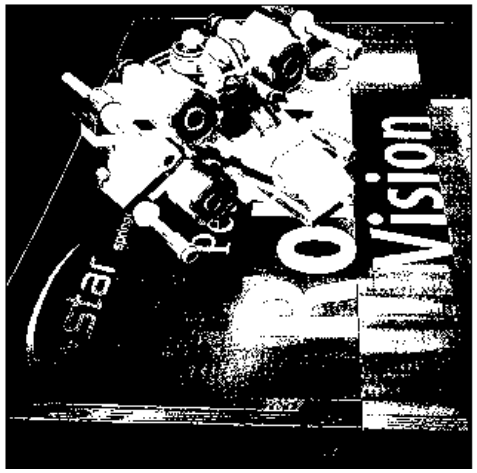
Background subtraction

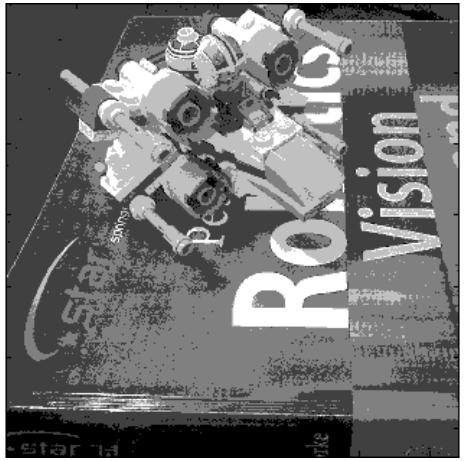
Code sample >

```
% backgorund estimation
sigma=0.01;
vid = videoinput('winvideo', 1);
bg=getsnapshot(vid);
bg_small=idouble(imono(bg));
while 1
     img=getsnapshot(vid);
     img_small=idouble(imono(img));
     if isempty(img), break; end
     d=img_small-bg_small;
     d=max(min(d,sigma), -sigma);
     bg_small=bg_small+d;
     idisp(bg_small); drawnow
end
```

Thresholding and posterization







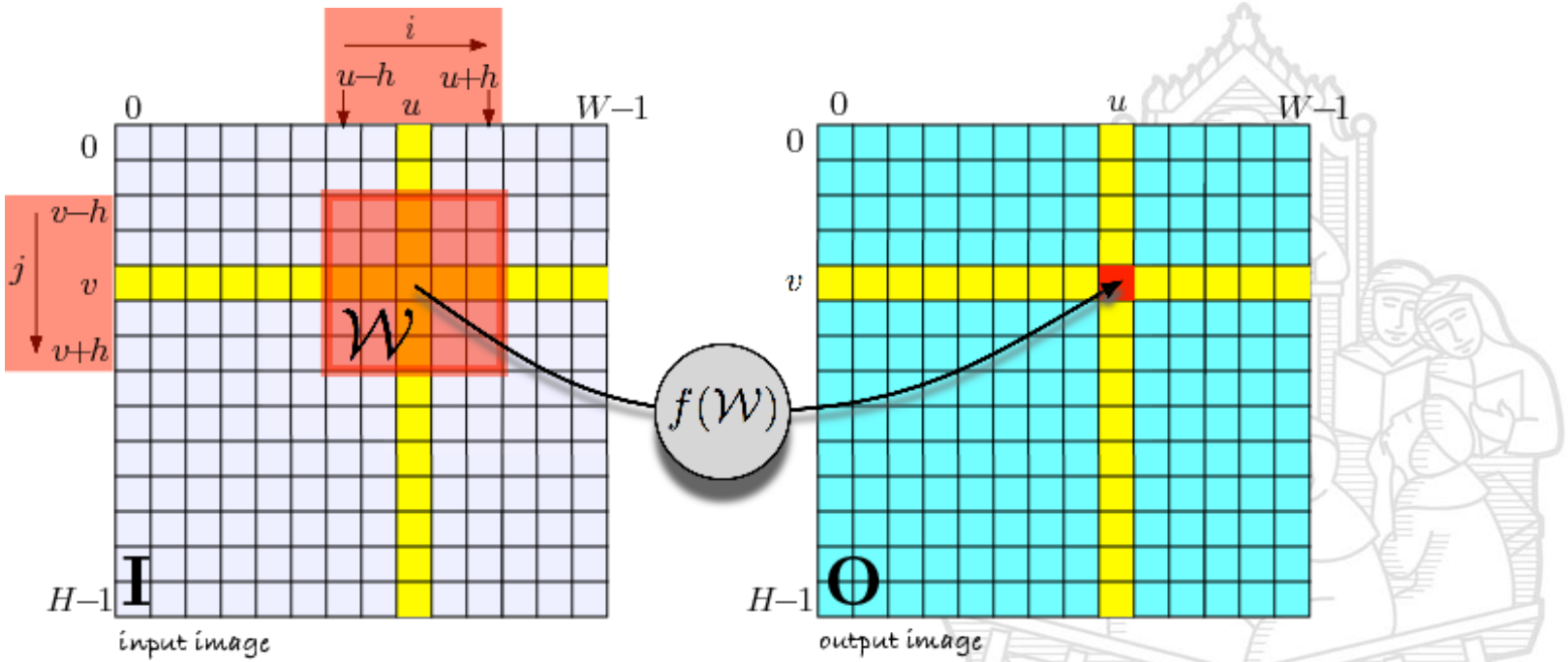
$$\boldsymbol{O}[u,v] = \begin{cases} 1, & if\ \boldsymbol{I}[u,v] > t \\ 0, & if\ \boldsymbol{I}[u,v] \leq t \end{cases}$$

Where t is the threshold, and 1 represents the maximum grey level value of the pixel

Merge several adjacent levels together

Spatial operation (local operators)

$$\boldsymbol{O}[u,v] = f(\boldsymbol{I}[u+i, v+j]), \qquad \forall (i,j) \in \boldsymbol{W}, \forall (u,v) \in \boldsymbol{I}$$



Correlazione e convoluzione

Immaginiamo di avere una immagine “monodimensionale”, oppure una sola linea di una immagine

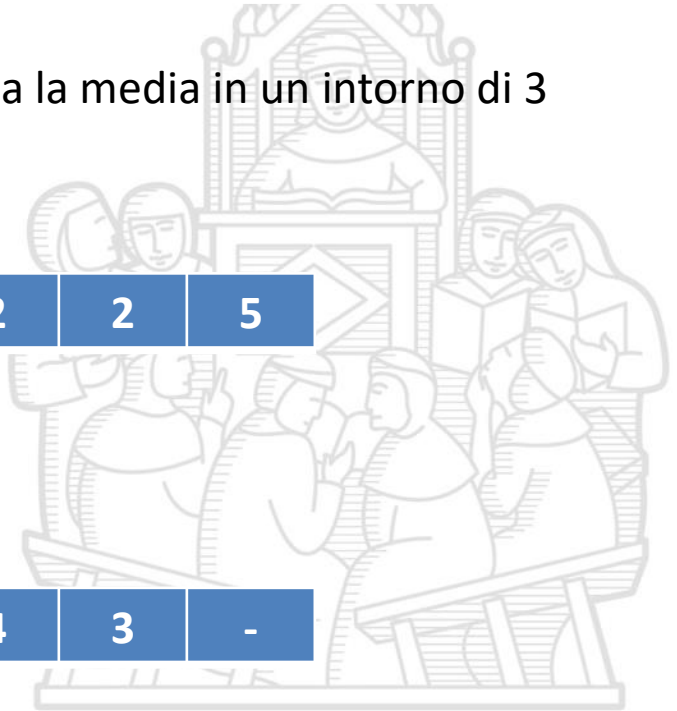
I =	2	2	5	2	5	8	8	2	2	5

Supponiamo di voler creare una nuova immagine **O** che sia la media in un intorno di 3 pixel dell’immagine originale **I**.

2	2	5	2	5	8	8	2	2	5

$$O(2) = \frac{I(1) + I(2) + I(3)}{3}$$

O =	-	3	3	4	5	7	6	4	3	-



Effetti di bordo

Dovrebbe essere subito venuto all'occhio un problema: cosa succede nei bordi?

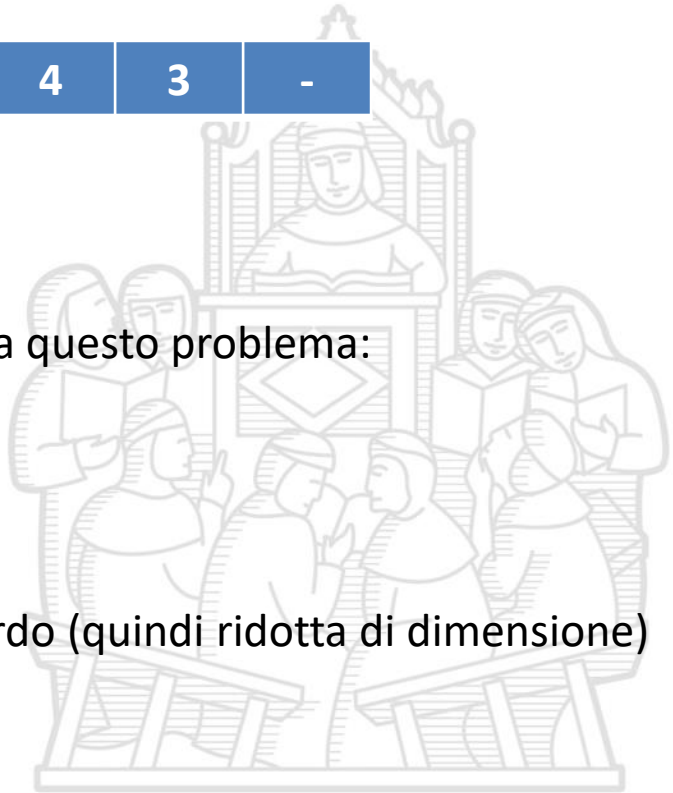
I =	2	2	5	2	5	8	8	2	2	5

O =	-	3	3	4	5	7	6	4	3	-

I(0) non esiste, per cui ***O(1)*** non può essere definito.

Generalmente vengono usati quattro metodi per ovviare a questo problema:

1. L'immagine I viene estesa con degli zero
2. L'immagine I viene estesa con l'ultimo valore di bordo
3. L'immagine I viene ripetuta in maniera ciclica
4. L'immagine O viene considerata non definita per il bordo (quindi ridotta di dimensione)

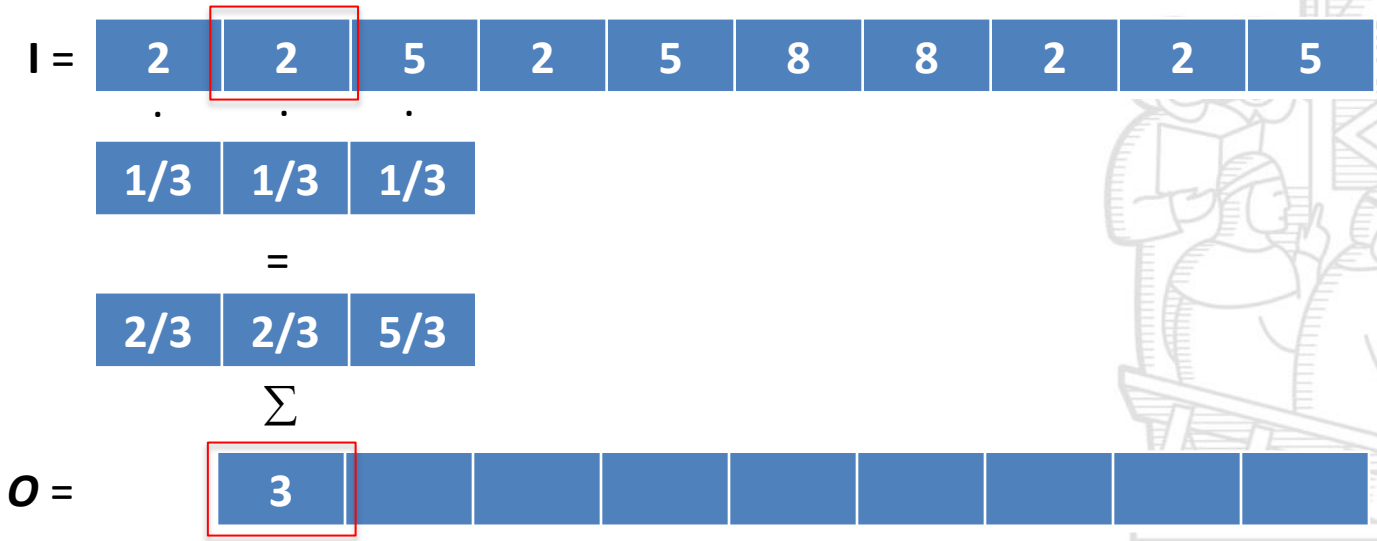


Correlazione

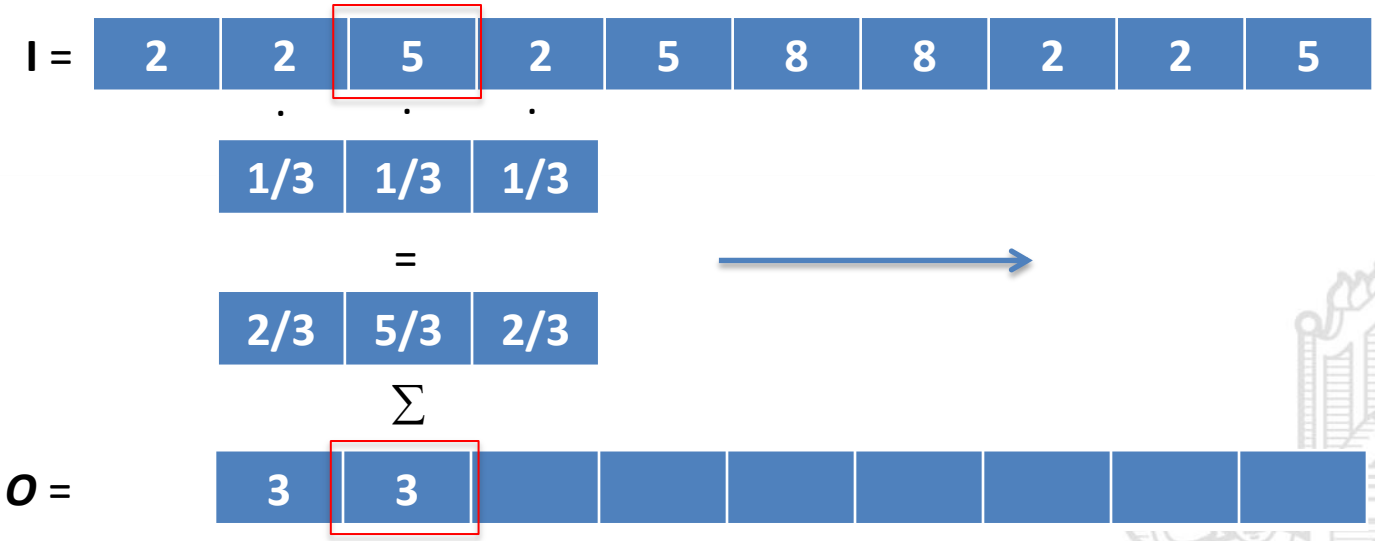
Vediamo l'operazione di media con una vesta grafica, un po' più intuitiva da generalizzare

Nell'operazione di media che abbiamo visto, noi moltiplichiamo un certo pixel e i valori adiacenti per 1/3, quindi sommiamo i tre valori tra loro.

Possiamo chiamare i tre valori che moltiplichiamo (1/3, 1/3, 1/3) come un **filtro** che facciamo scorrere su tutta l'immagine



Correlazione



Correlazione

Scrivendo una definizione formale, possiamo definire la correlazione come:

$$F \circ I(x) = \sum_{i=-N}^{N} F(i) \cdot I(x+i)$$

Dove F è il filtro di correlazione, che ha $2N+1$ elementi (dispari) con centro in $F(0)$, mentre I è l'immagine.

Il filtro per la media, è semplicemente definito come:

$$F(i) = \begin{cases} 1/3 & \textit{per} \quad i=-1, 0, 1 \\ 0 & \textit{altrimenti} \end{cases}$$

E' immediata l'estensione a una qualsiasi funzione continua che può essere discretizzata ed essere usata come filtro

Derivate discrete

Intuitivamente, la derivata misura la variazione di una funzione rispetto due posizioni della funzione stessa. Rigorosamente, la derivata è definita per funzioni continue, tuttavia possiamo implementarne una sua versione discreta, per esempio attraverso un filtro.

D =	-1/2	0	1/2

Che realizzerebbe nell'immagine di uscita:

$$O(i) = \frac{I(i+1) - I(i-1)}{2}$$

Derivate discrete

Consideriamo un vettore di esempio, $I(i)=i^2$

I =	1	4	9	16	25	36	49	64	81	100

. . .

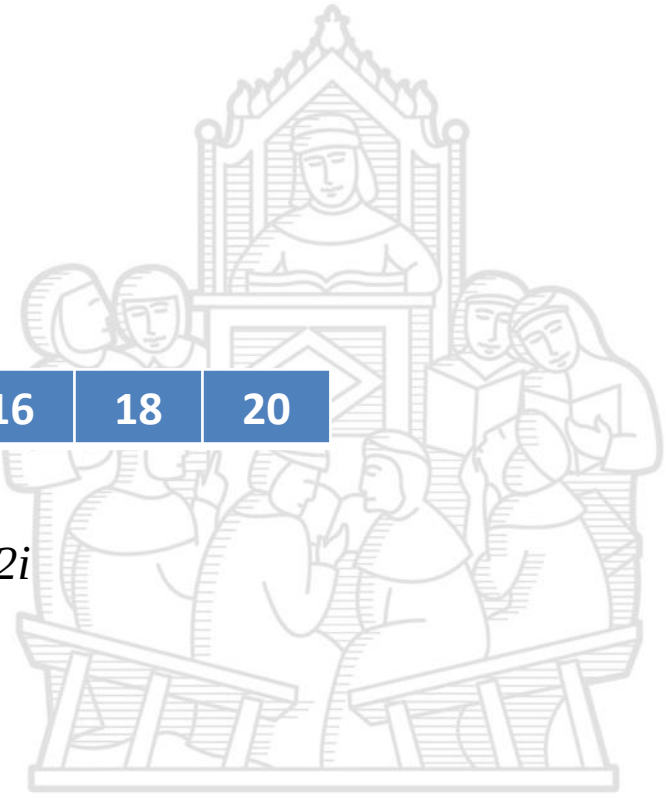
-1/2	0	1/2

=

-1/2	0	9/2

$\sum$

O =	4	6	8	10	12	14	16	18	20



Ed effettivamente $O(i)=2i$

Convoluzione

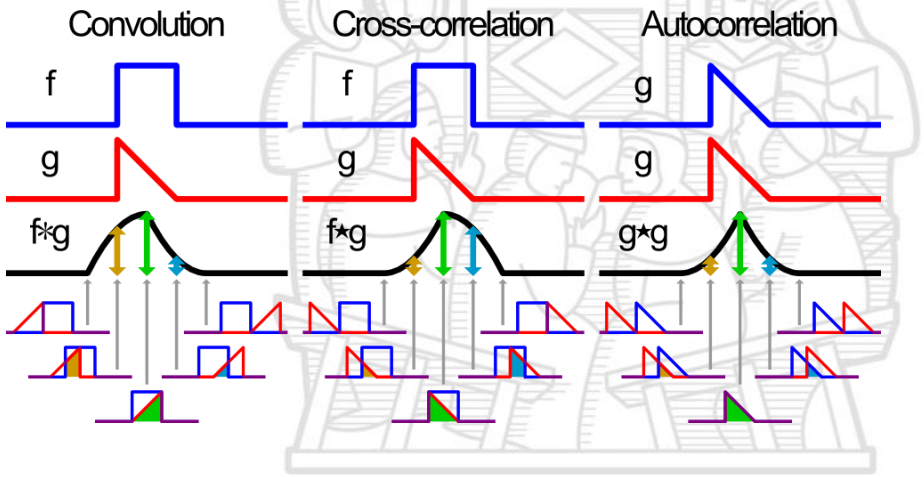
La convoluzione è molto simile alla correlazione: la differenza sta nel fatto che il filtro (o l'altro segnale) viene *invertito* prima di correlarlo.

In pratica, la convolulzione con un filtro (3, 7, 5) è esattamente la stessa cosa che effettuare una correlazione con il filtro (5, 7, 3)

La convoluzione discreta monodimensionale prende la forma di:

$$F \otimes I(x) = \sum_{i=-N}^{N} F(i) \cdot I(x-i)$$

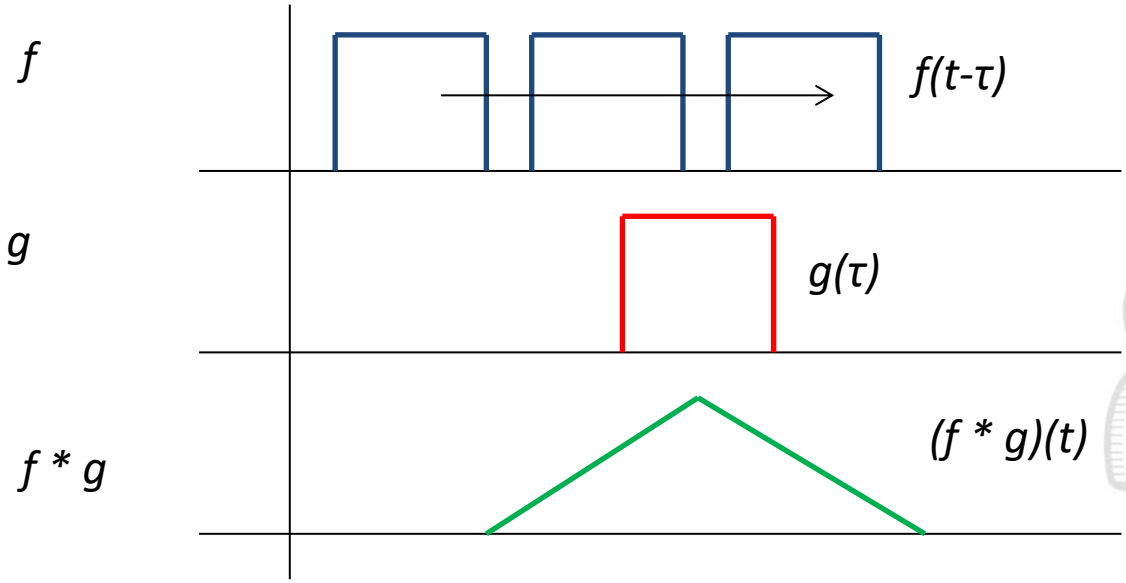
La differenza chiave tra le due è che la convoluzione gode della proprietà **associativa**

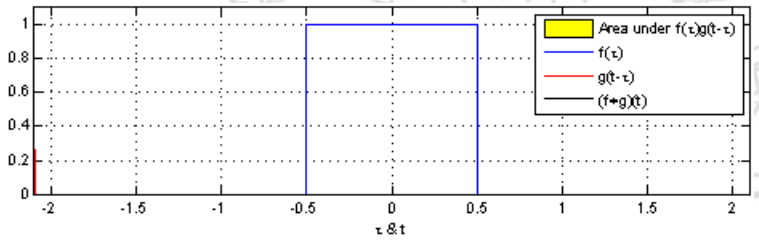


1D Convolution

One important local operator is the convolution:

$$(f * g)(t) := \int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau$$



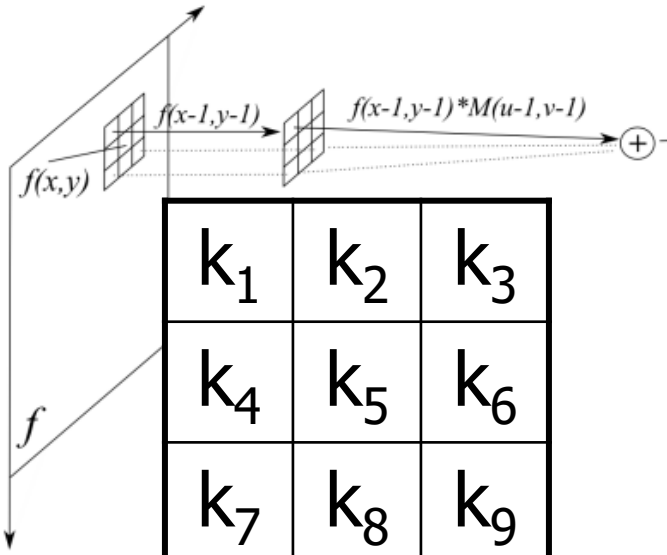


wikipedia

2D Convolution

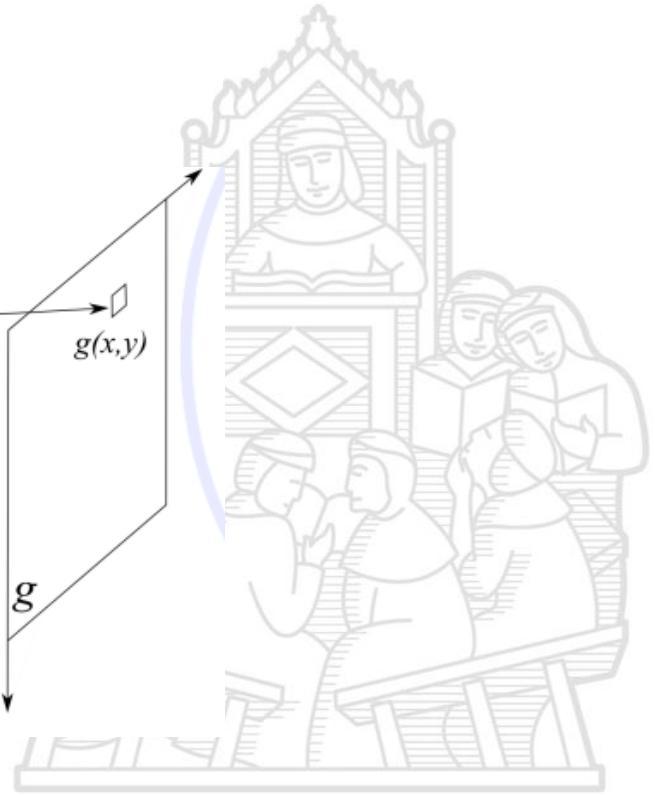
$$\boldsymbol{O}[u,v] = \sum_{i,j \in \boldsymbol{K}} \boldsymbol{K}[i,j]\boldsymbol{I}[u-i, v-j], \qquad \forall (u,v) \in \boldsymbol{I}$$

$$\boldsymbol{O} = \boldsymbol{K} \otimes \boldsymbol{I}$$



k_1	k_2	k_3
k_4	k_5	k_6
k_7	k_8	k_9

Convolution mask



2D Convolution

kernel

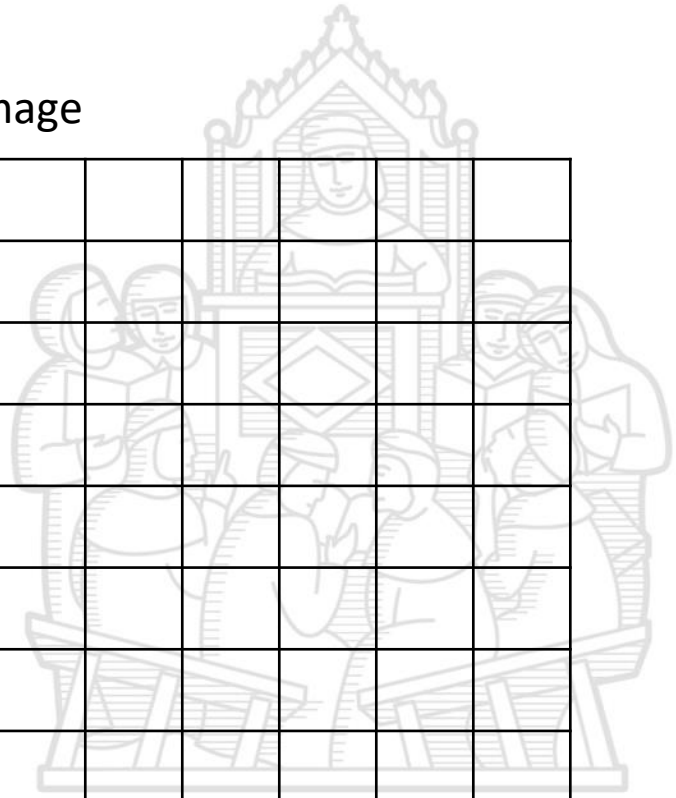
·1+	·1+	·1+
·1+	·1+	·1+
·1+	·1+	·1

Input image

0	1	2	0	12	5	0	1
5	2	6	0	0	1	1	1
5	0	0	4	5	6	1	0
12	25	0	24	56	8	2	3
1	2	6	0	0	1	5	2
1	2	0	2	1	2	1	0
12	0	12	25	3	5	0	1
1	1	1	35	57	5	3	1

Output image

	21						



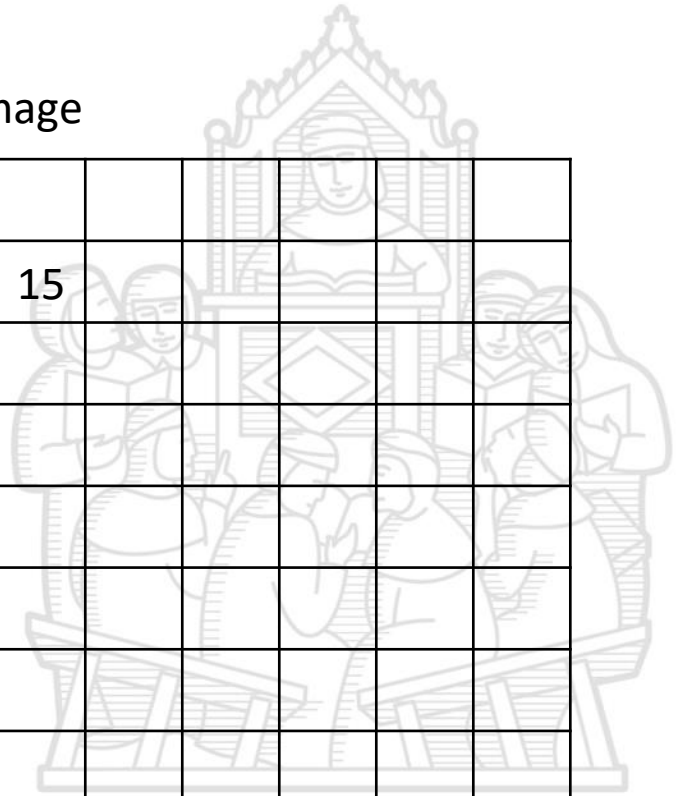
Convolution

Input image

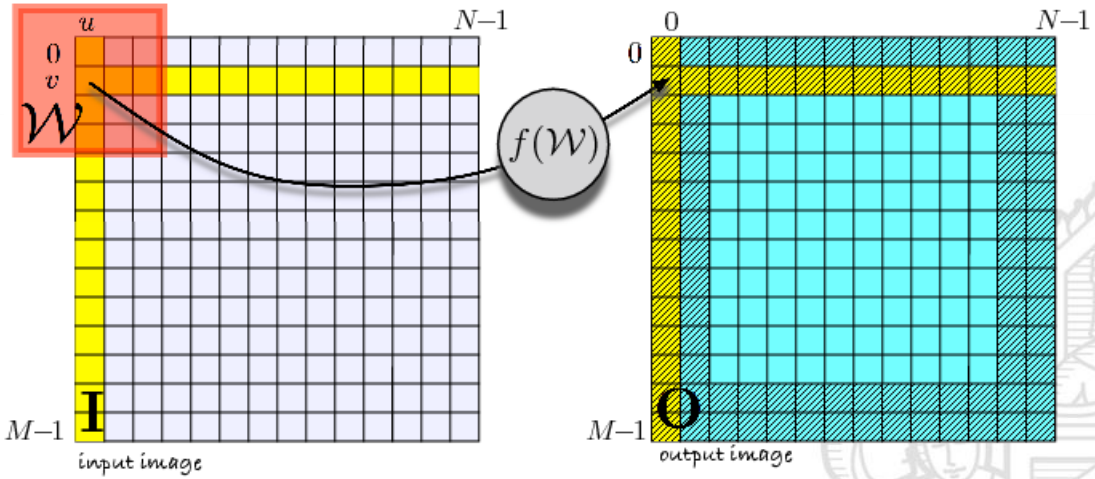
0·1+	1·1+	2·1+	0	12	5	0	1
5·1+	2·1+	6·1+	0	0	1	1	1
5·1+	0·1+	0·1	4	5	6	1	0
12	25	0	24	56	8	2	3
1	2	6	0	0	1	5	2
1	2	0	2	1	2	1	0
12	0	12	25	3	5	0	1
1	1	1	35	57	5	3	1

Output image

	21	15					

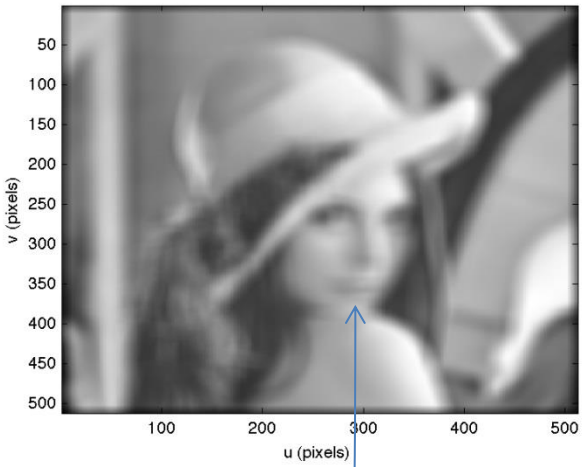


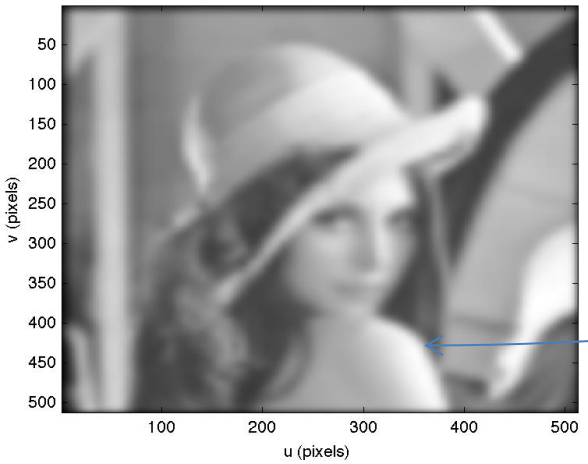
Boundary effect



- Duplicate
- All black
- Reduce size
- …

Smoothing



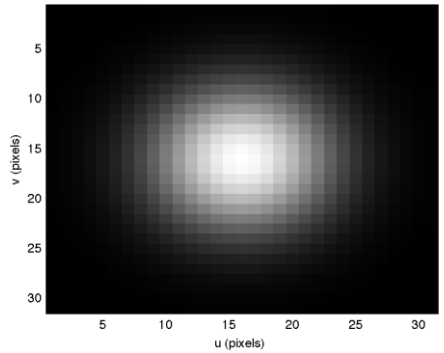


$$K = ones(21, 21)/21^2$$

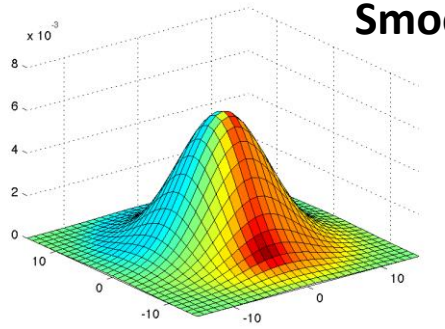
$$O = K \otimes I$$

$$G[u, v] = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$

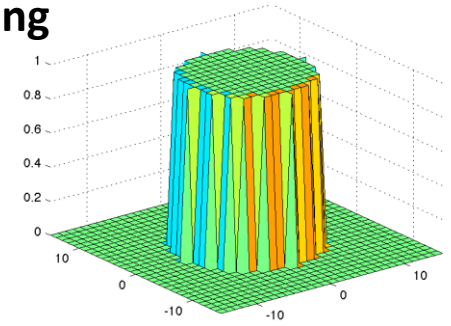
Kernel examples



Smoothing

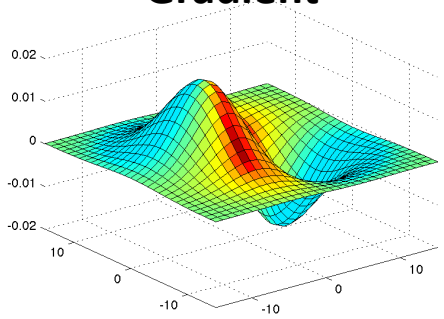


Gaussian



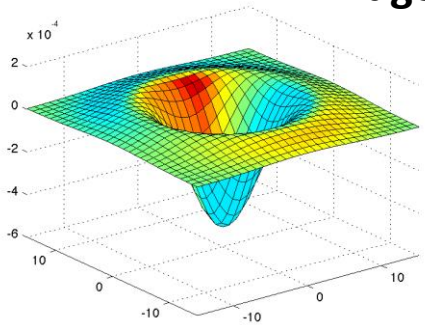
Top hat

Gradient

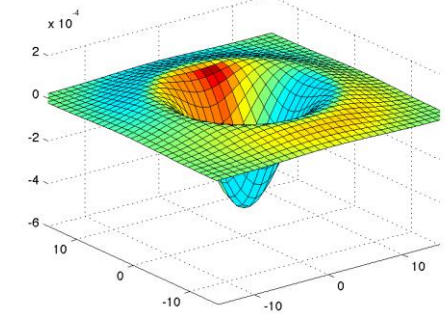


Derivative of Gaussian (DoG)

Edge detection

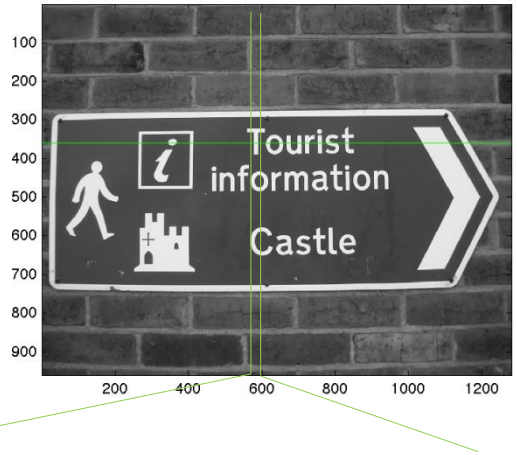


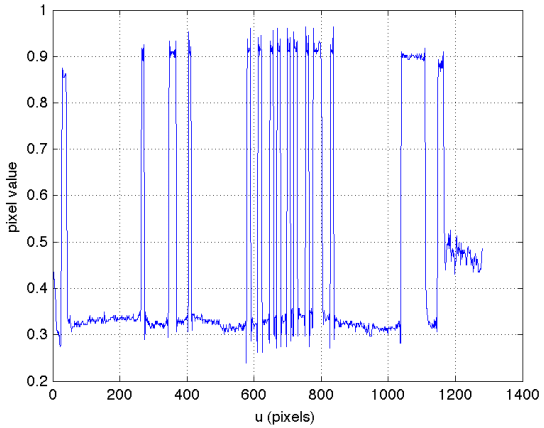
Laplacian of Gaussian (LoG)



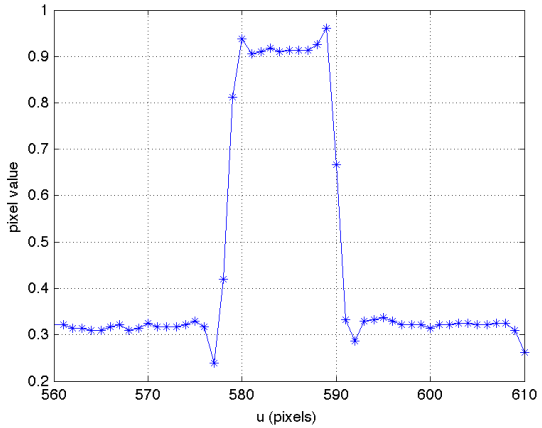
Difference of Gaussian (DiffG)

Edge detection





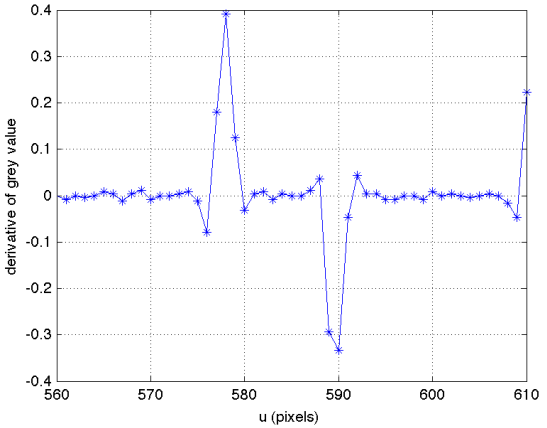
Horizontal profile of the image at *v*=360



$$p'[u] = p[u] - p[u-1]$$

$$p'[u] = \frac{1}{2}(p[u+1] - p[u-1])$$

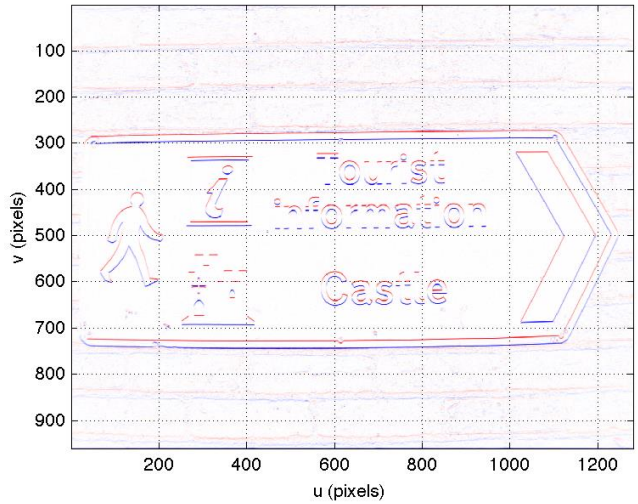
$$\boldsymbol{K} = \left[-\frac{1}{2} \quad 0 \quad \frac{1}{2}\right]$$

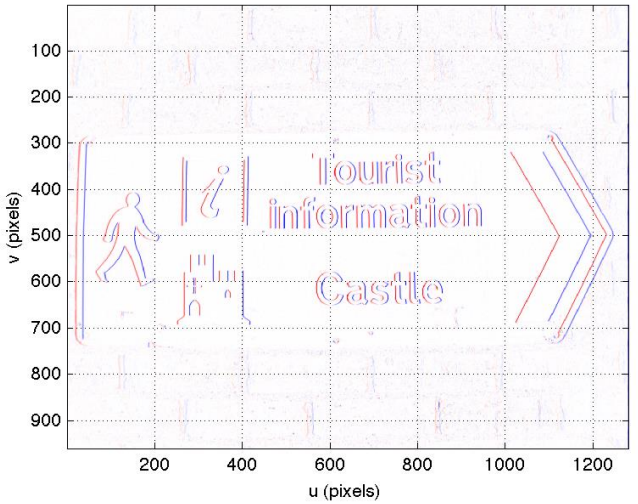


Gradient computation

Common convolution kernel: Sobel, Prewitt, Roberts, …

Sobel $\boldsymbol{D}_v = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$ $\boldsymbol{D}_u = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$



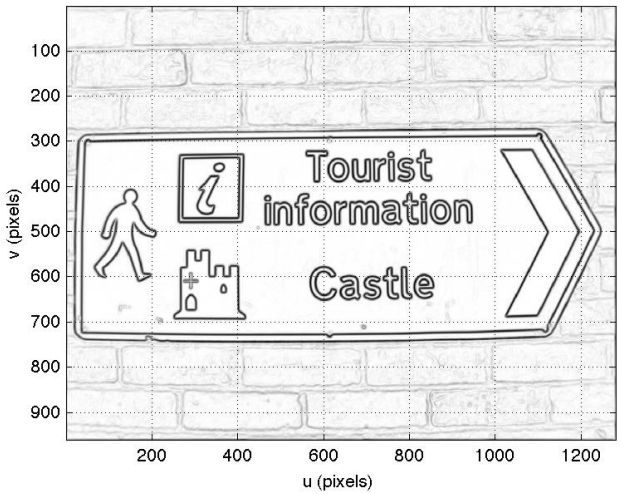


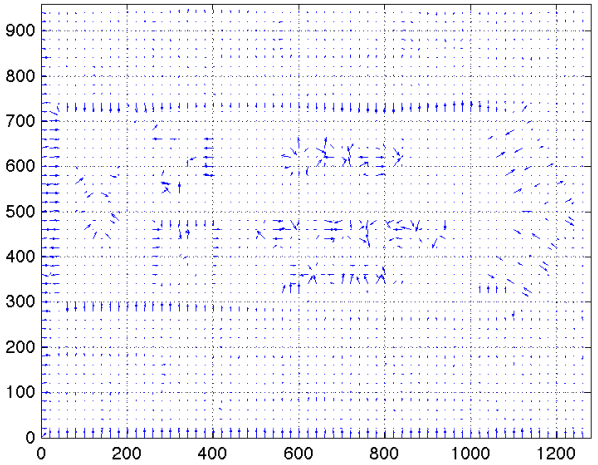
$\boldsymbol{I}_v = \boldsymbol{D}_v \otimes \boldsymbol{I}$ $\boldsymbol{I}_u = \boldsymbol{D}_u \otimes \boldsymbol{I}$

Direction and magnitude

$$m = \sqrt{\boldsymbol{I}_v^2 + \boldsymbol{I}_u^2}$$

$$\theta = \text{atan}(\boldsymbol{I}_v, \boldsymbol{I}_u)$$





Noise amplification

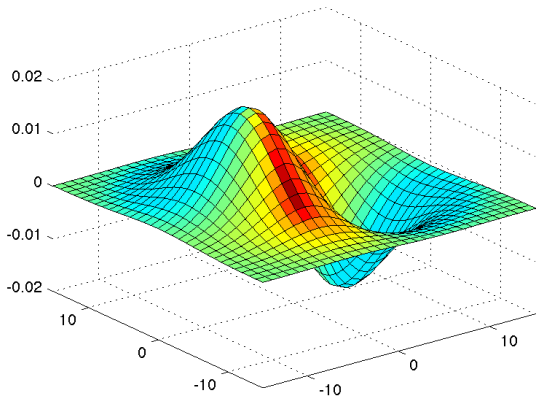
Derivative amplifies high-frequency noise. So, firstly we can smooth the image, after that we can take the derivative:

$$\boldsymbol{I}_u = \boldsymbol{D}_u \otimes (\boldsymbol{G} \otimes \boldsymbol{I})$$

Associative property:

$$\boldsymbol{I}_u = \underbrace{(\boldsymbol{D}_u \otimes \boldsymbol{G})}_{\text{Derivative of Gaussian (DoG)}} \otimes \boldsymbol{I}$$

$$\boldsymbol{G}_u = -\frac{u}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



Derivative of Gaussian (DoG)

<<DoG acts as a bandpass filter!>>

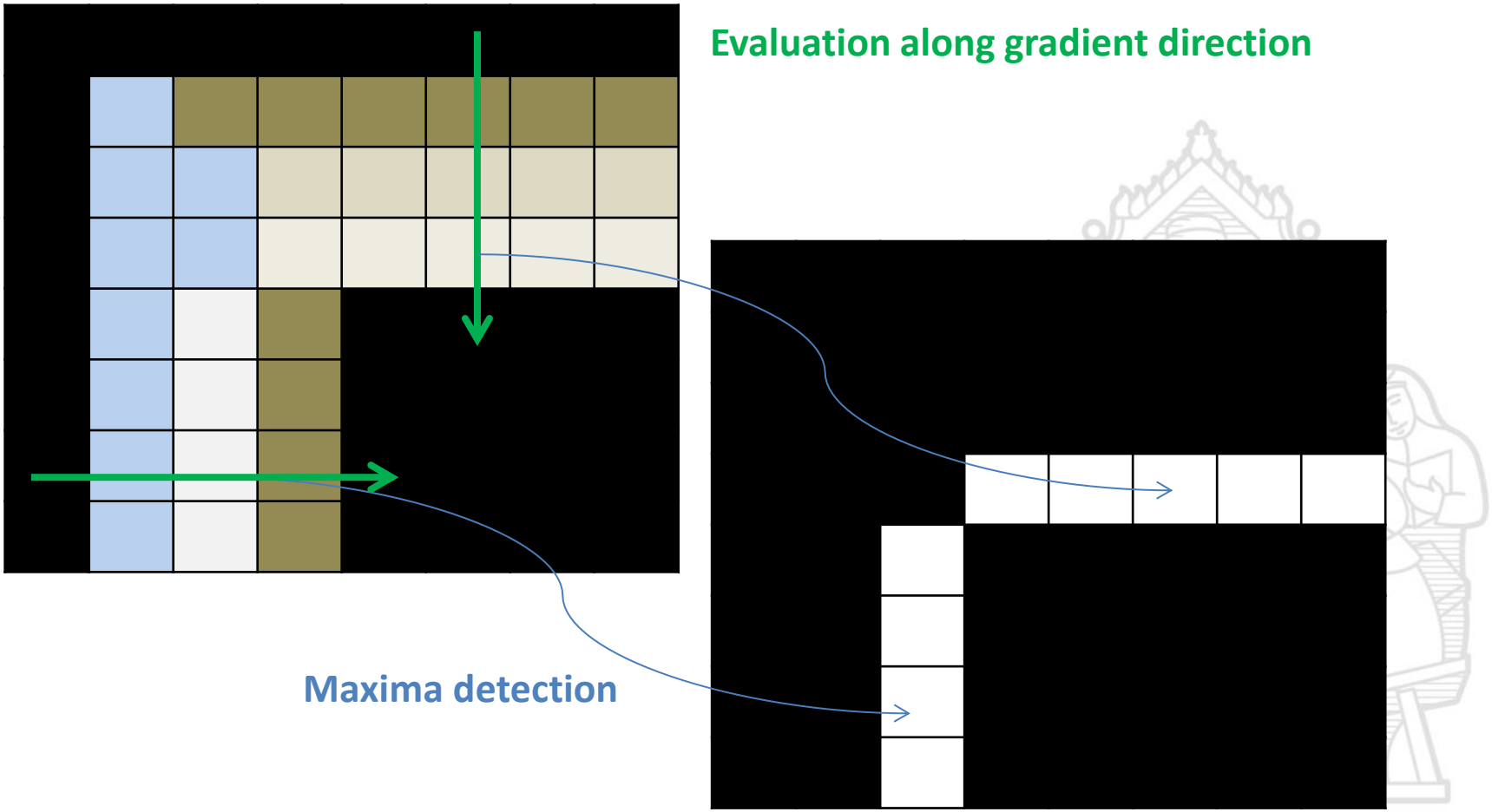
Canny edge detection

The algorithm is based on a few steps:

1. Gaussian filtering
2. Gradient intensity and direction
3. non-maxima suppression (edge thinning)
4. hysteresis threshold

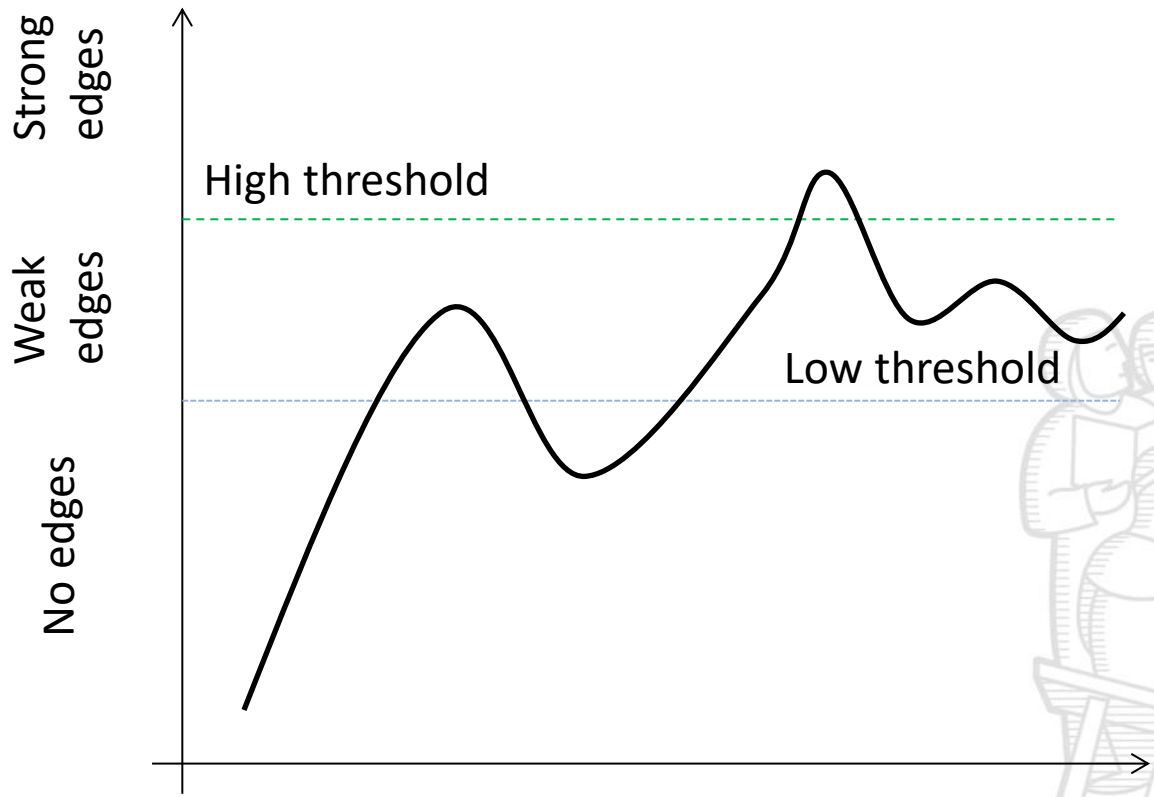
Canny edge detection

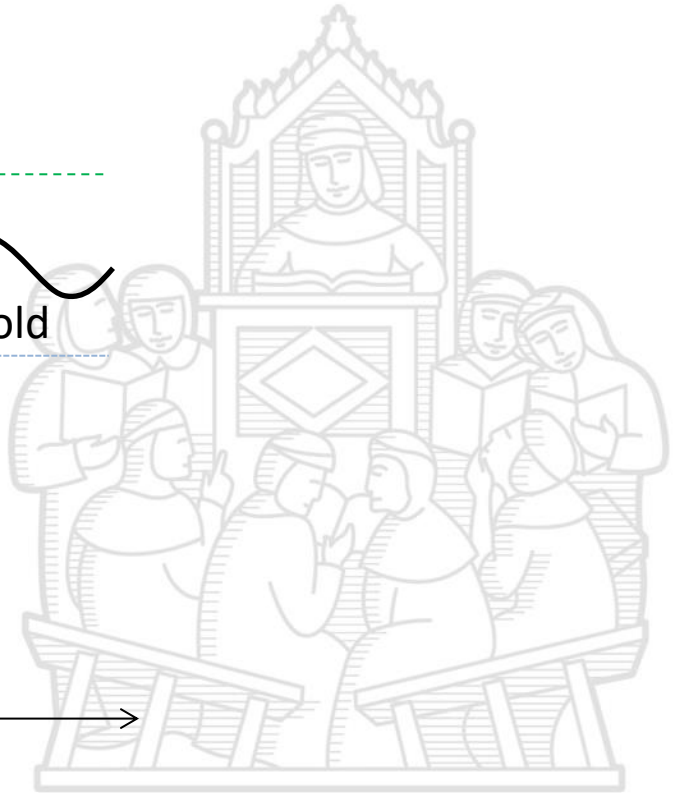
3. Non local maxima suppression



Canny edge detection

4. hysteresis threshold

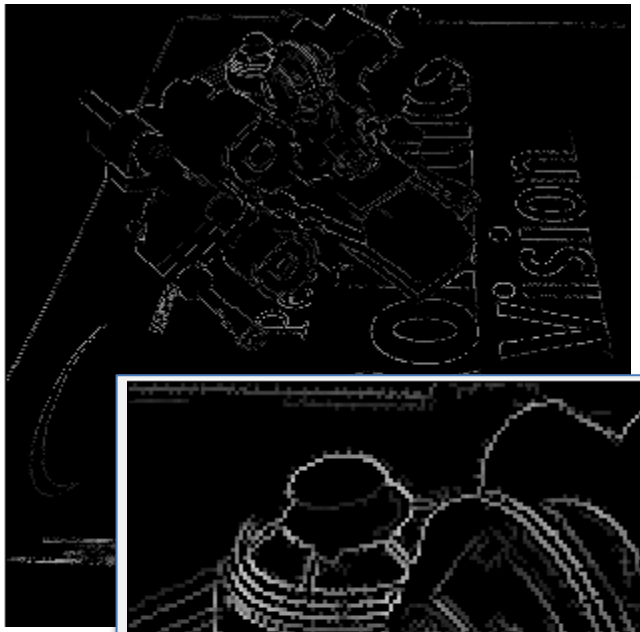


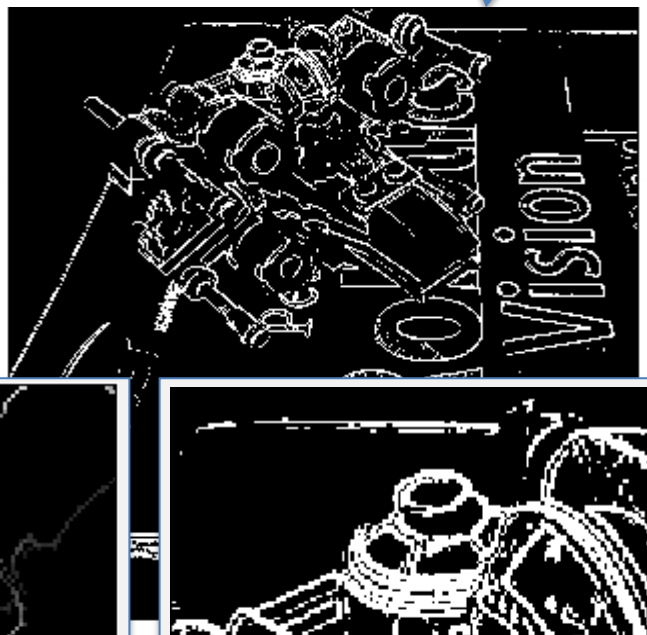


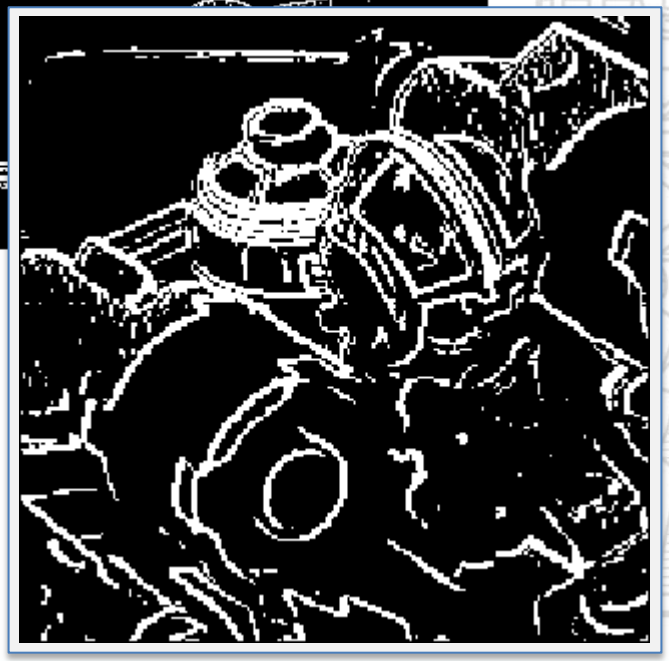
Magnitude of the gradient

Thresholding

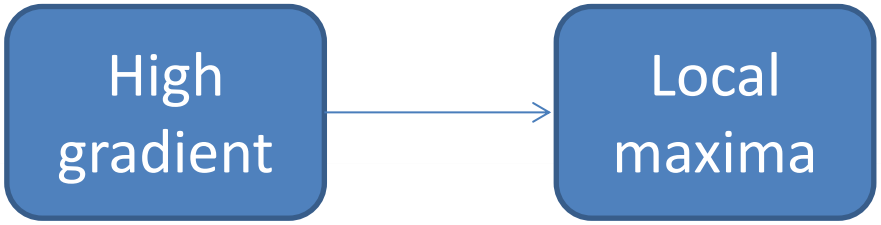
canny







Edge detection

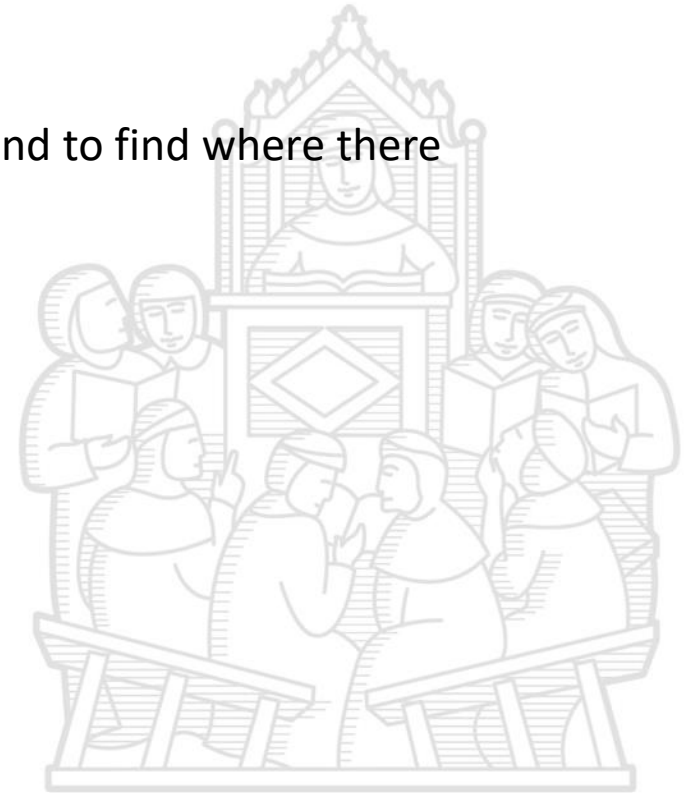


Alternative approach is to use second derivative and to find where there is a zero

Laplacian operator

$$\nabla \boldsymbol{I}^2 = \frac{\partial^2 \boldsymbol{I}}{\partial u^2} + \frac{\partial^2 \boldsymbol{I}}{\partial v^2} = \boldsymbol{I}_{uu} + \boldsymbol{I}_{vv} = \boldsymbol{L} \otimes \boldsymbol{I}$$

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



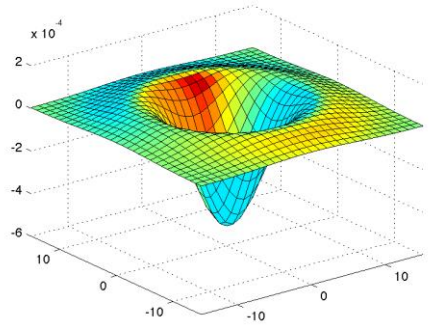
Noise sensitivity

Again, derivative amplifies high-frequency noise. So firstly we can smooth the image, after that we take the derivative:

$$\boldsymbol{L} \otimes (\boldsymbol{G} \otimes \boldsymbol{I}) = \underbrace{(\boldsymbol{L} \otimes \boldsymbol{G})} \otimes \boldsymbol{I}$$

Laplacian of Gaussian (LoG)

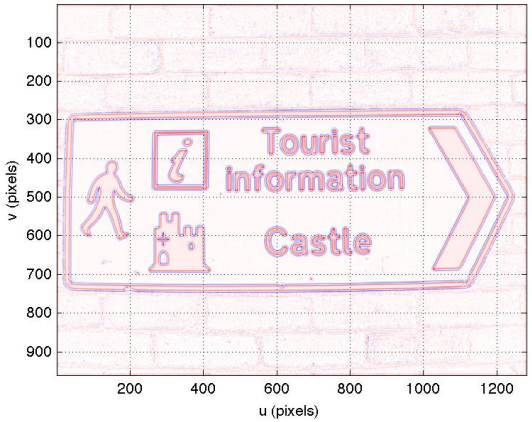
$$\boldsymbol{LoG}(u,v) = \frac{1}{\pi\sigma^4}\left(\frac{u^2+v^2}{2\sigma^2} - 1\right) e^{-\frac{u^2+v^2}{2\sigma^2}}$$

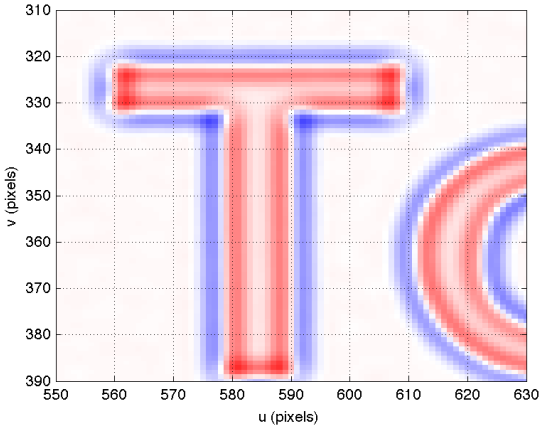


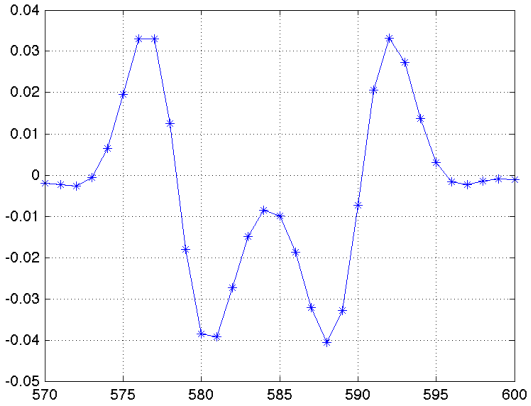
Laplacian of Gaussian (LoG)

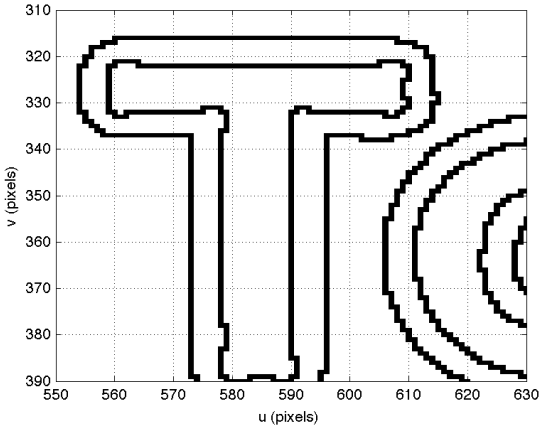
Marr-Hildreth operator or the Mexican hat kernel

Edge detection









Gradient and Laplacian

Example

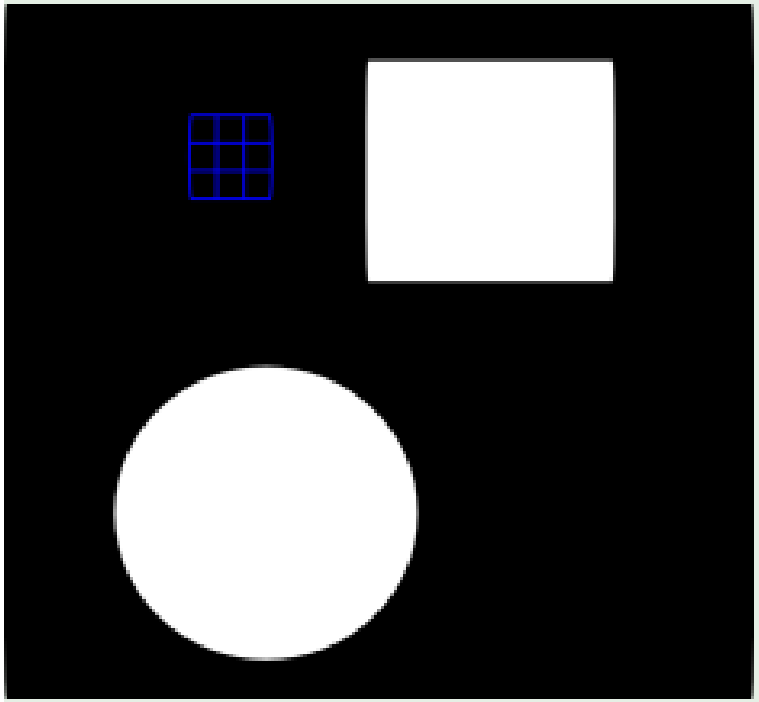


Image window:

$f(x, y)$ =

0	0	0
0	0	0
0	0	0

∇^2 =

0	-1	0
-1	4	-1
0	-1	0

G_x =

-1	0	1
-2	0	2
-1	0	1

Products are:

$$\nabla^2 \otimes f(x, y) = 0$$

$$G_x \otimes f(x, y) = 0$$

Gradient and Laplacian

Example

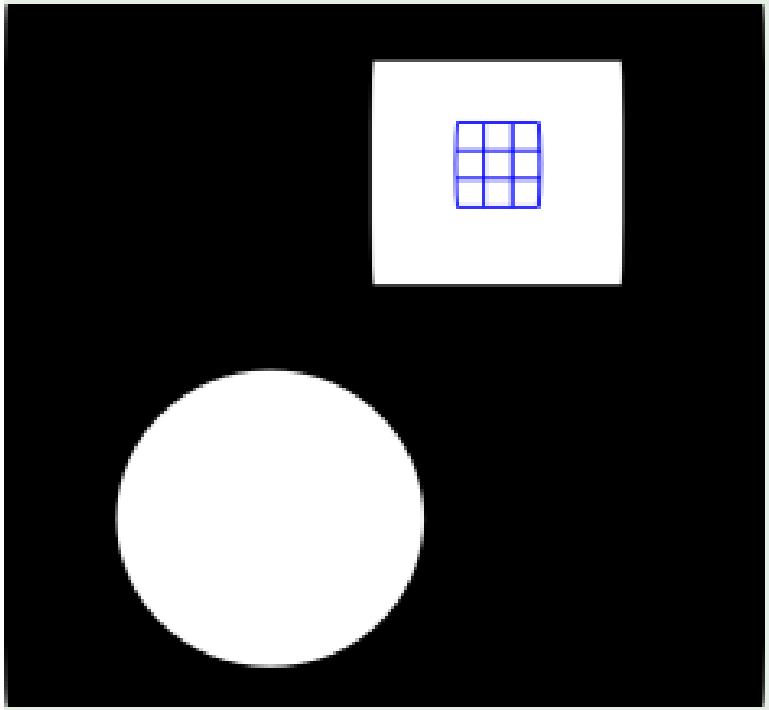


Image window:

$f(x, y)$ =

1	1	1
1	1	1
1	1	1

∇^2 =

0	-1	0
-1	4	-1
0	-1	0

G_x =

-1	0	1
-2	0	2
-1	0	1

Products are:

$$\nabla^2 \otimes f(x, y) = 0$$

$$G_x \otimes f(x, y) = 0$$

Gradient and Laplacian

Example

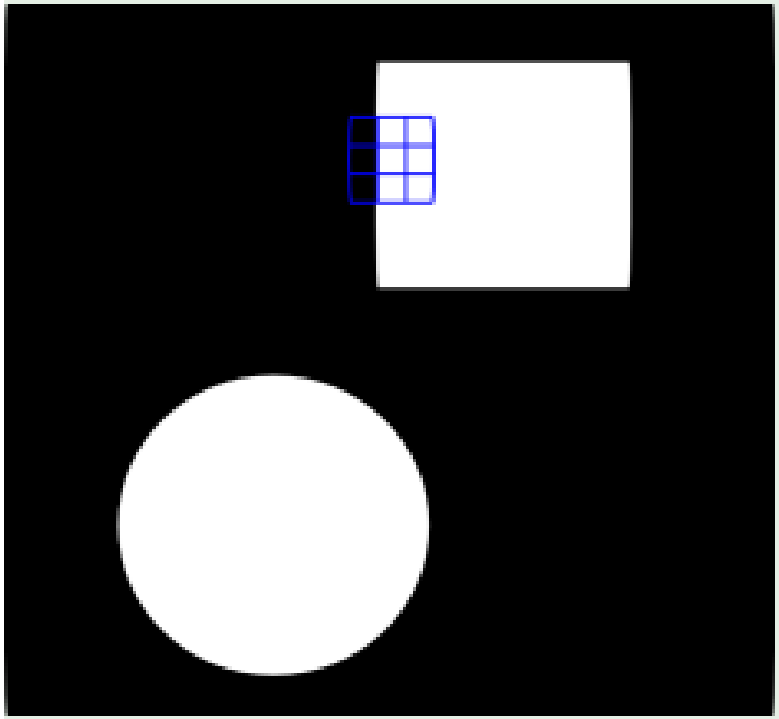


Image window:

$f(x, y)$ =

0	1	1
0	1	1
0	1	1

∇^2 =

0	-1	0
-1	4	-1
0	-1	0

G_x =

-1	0	1
-2	0	2
-1	0	1

Products are:

$$\nabla^2 \otimes f(x, y) = 1$$
$$G_x \otimes f(x, y) = 4$$

Gradient and Laplacian

Example

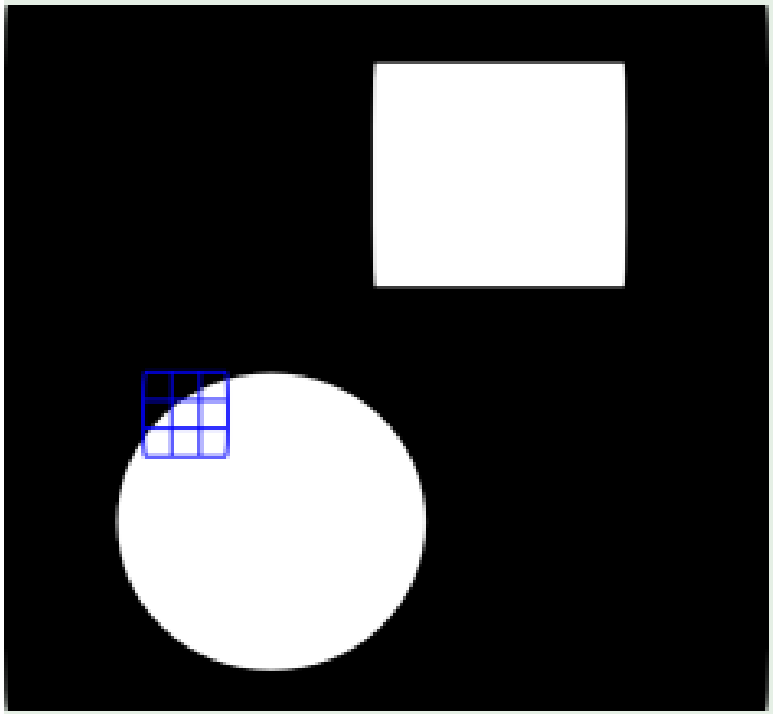


Image window:

$f(x, y)$ =

0	0	1
0	1	1
1	1	1

∇^2 =

0	-1	0
-1	4	-1
0	-1	0

G_x =

-1	0	1
-2	0	2
-1	0	1

Products are:

$$\nabla^2 \otimes f(x, y) = 2$$

$$G_x \otimes f(x, y) = 3$$

Gradient and Laplacian

Example

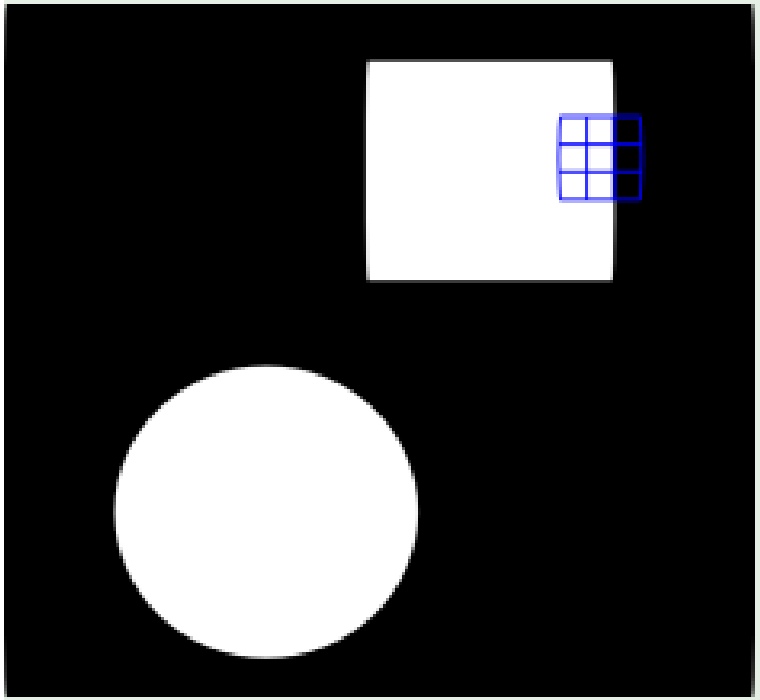


Image window:

$f(x, y)$ =

1	1	0
1	1	0
1	1	0

∇^2 =

0	-1	0
-1	4	-1
0	-1	0

G_x =

-1	0	1
-2	0	2
-1	0	1

Products are:

$$\nabla^2 \otimes f(x, y) = 1$$

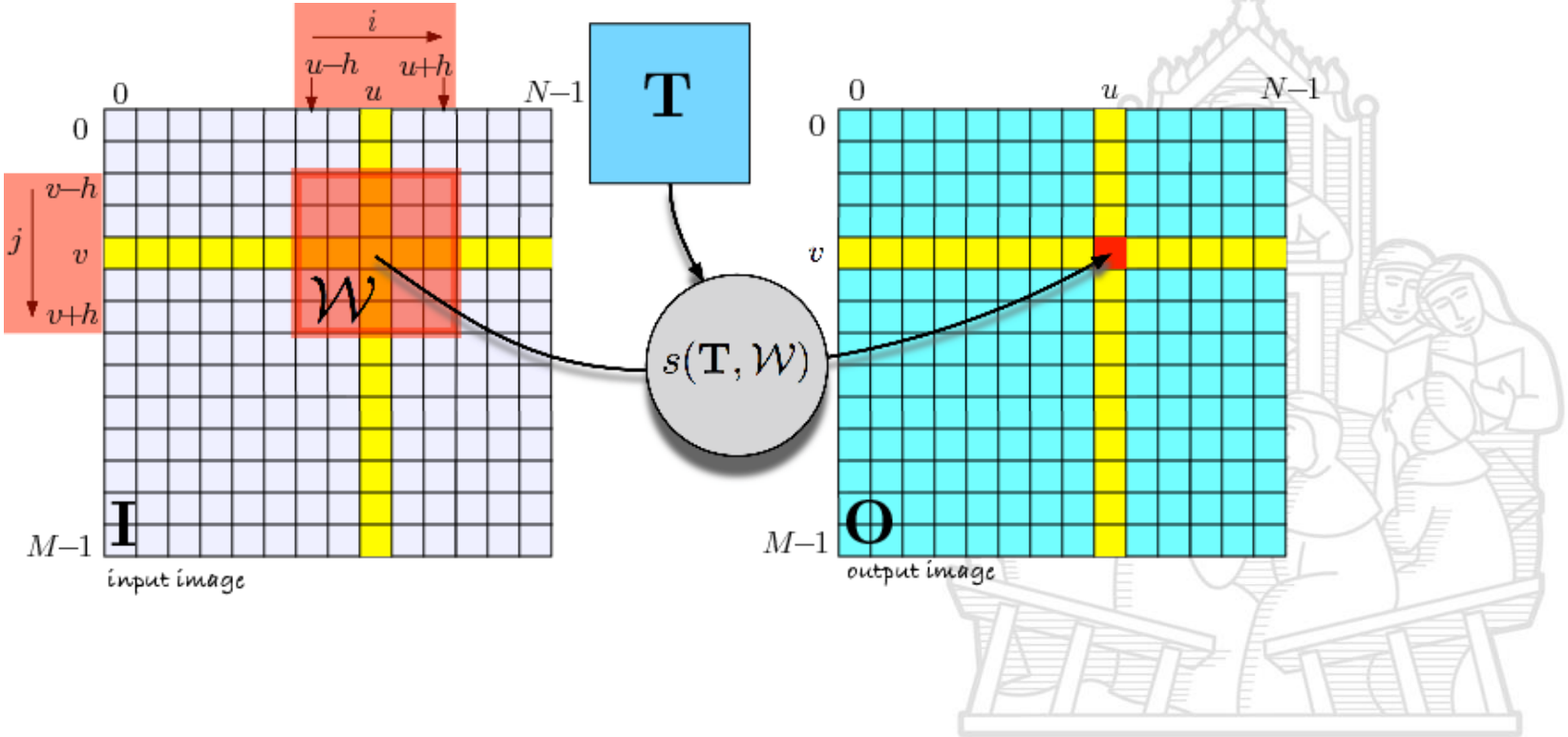
$$G_x \otimes f(x, y) = -4$$

Code sample >

```
% denoising/edge detection
dx=[-1 0 1;-2 0 1; -1 0 1];
dy=[-1 -2 -1;0 0 0;1 2 1];
K=kgauss(3);
K1=ones(19,19).*1/(19*19);
xwingDenoisMean=iconv(K1,xwing_grey);
idisp(xwingDenoisMean)
xwingDenoisGaus=iconv(K,xwing_grey);
idisp(xwingDenois)
xwingIx=iconv(dx,xwing_grey);
idisp(xwingIx)
xwingIy=iconv(dy,xwing_grey);
idisp(xwingIy)
magnGrad=sqrt(xwingIx.^2+xwingIy.^2);
idisp(magnGrad)
edgeGrad=magnGrad>250;

edgeLapl=iconv(klog(2),xwing_grey);
idisp(iint(edgeLapl)>250);

edgeLapl=iconv(klog(1),xwing_grey);
idisp(iint(edgeLapl)>250);

edgeLapl=iconv(klog(3),xwing_grey);
idisp(iint(edgeLapl)>250);
```

Template matching

$$\boldsymbol{O}[u,v] = s(\boldsymbol{T}, W), \qquad \forall (u,v) \in \boldsymbol{I}$$



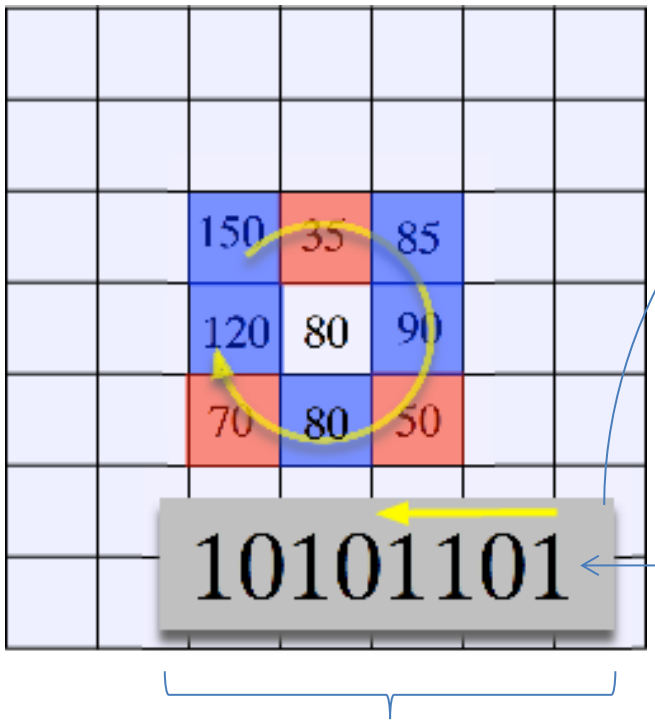
Template matching

Similarity measures

Sum of absolute differences	
SAD	$s = \sum_{(u,v)\in \boldsymbol{I}} \lvert \boldsymbol{I}_1[u,v] - \boldsymbol{I}_2[u,v] \rvert$
ZSAD	$s = \sum_{(u,v)\in \boldsymbol{I}} \lvert (\boldsymbol{I}_1[u,v] - \bar{\boldsymbol{I}_1}) - (\boldsymbol{I}_2[u,v] - \bar{\boldsymbol{I}_2}) \rvert$
Sum of squared differences	
SSD	$s = \sum_{(u,v)\in \boldsymbol{I}} (\boldsymbol{I}_1[u,v] - \boldsymbol{I}_2[u,v])^2$
ZSSD	$s = \sum_{(u,v)\in \boldsymbol{I}} ((\boldsymbol{I}_1[u,v] - \bar{\boldsymbol{I}_1}) - (\boldsymbol{I}_2[u,v] - \bar{\boldsymbol{I}_2}))^2$
Cross correlation	
NCC	$s = \frac{\sum_{(u,v)\in \boldsymbol{I}} \boldsymbol{I}_1[u,v] \cdot \boldsymbol{I}_2[u,v]}{\sqrt{\sum_{(u,v)\in \boldsymbol{I}} \boldsymbol{I}_1^2[u,v] \cdot \sum_{(u,v)\in \boldsymbol{I}} \boldsymbol{I}_2^2[u,v]}}$
ZNCC	$s = \frac{\sum_{(u,v)\in \boldsymbol{I}} (\boldsymbol{I}_1[u,v] - \bar{\boldsymbol{I}_1}) \cdot (\boldsymbol{I}_2[u,v] - \bar{\boldsymbol{I}_2})}{\sqrt{\sum_{(u,v)\in \boldsymbol{I}} (\boldsymbol{I}_1[u,v] - \bar{\boldsymbol{I}_1})^2 \cdot \sum_{(u,v)\in \boldsymbol{I}} (\boldsymbol{I}_2[u,v] - \bar{\boldsymbol{I}_2})^2}}$

Non-parametric similarity measures

Census



$$s(x) = \begin{cases} 1, if\ x > R \\ 0, otherwise \end{cases}$$

Census representation

Hamming distance

Rank transform = 5

Non-parametric similarity measures

Rank transform is more compact but does not encode position information

50	10	205
1	25	2
102	250	240

Census: 01110101

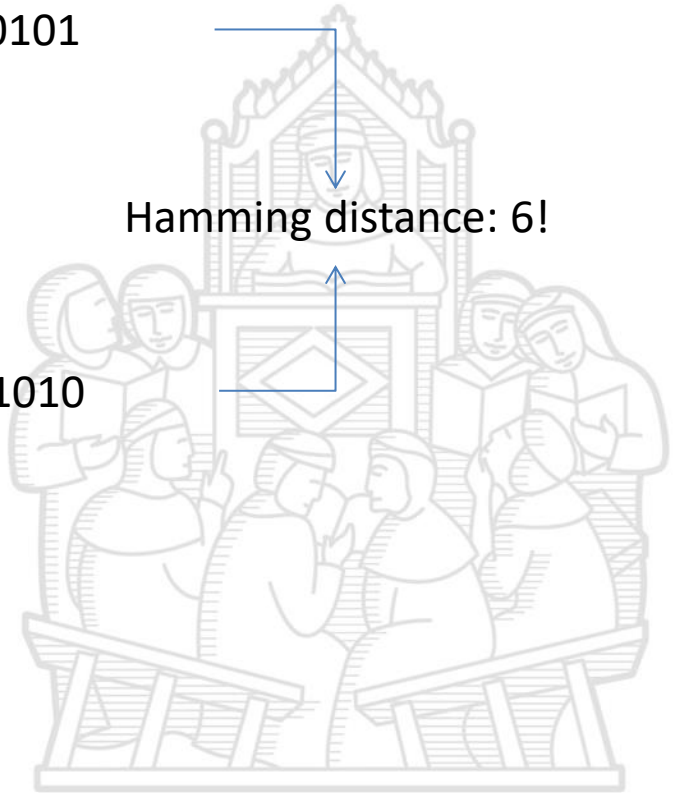
Rank: 5

10	26	2
101	25	202
1	250	214

Census: 10111010

Rank: 5

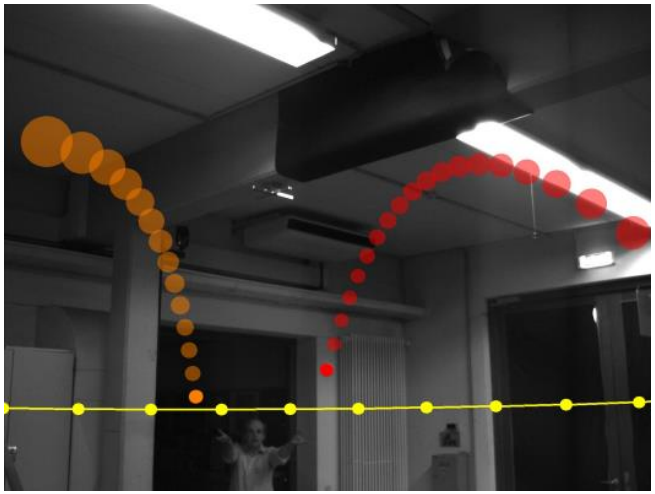
Hamming distance: 6!

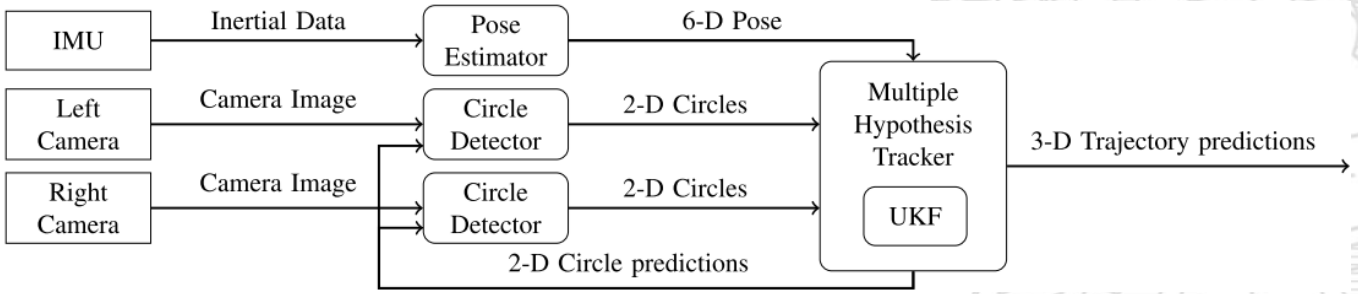


Non-linear operators

- Variance measure (on windows): Edge detection
- Median filter: noise removal
- Rank transform: non-local maxima suppression

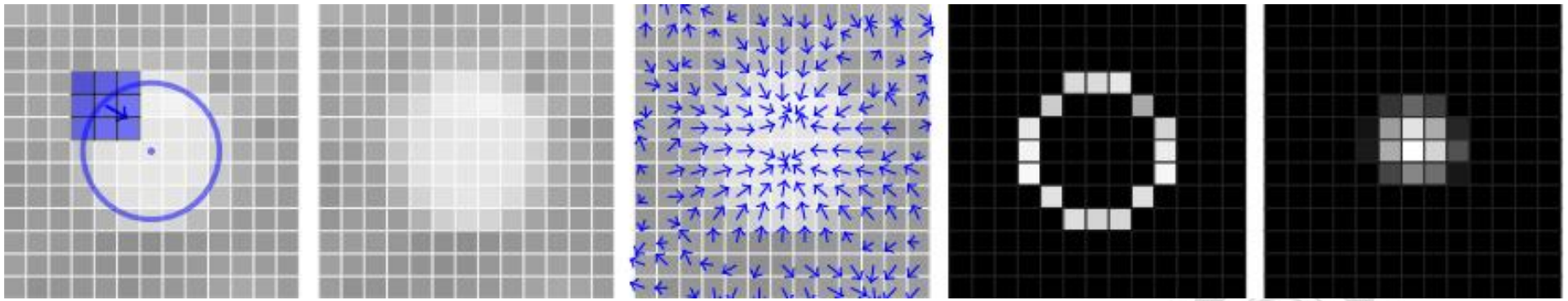
Example DLR





Oliver Birbach, Udo Frese and Berthold Bauml, (2011) 'Realtime Perception for Catching a Flying Ball with a Mobile Humanoid'

Example DLR

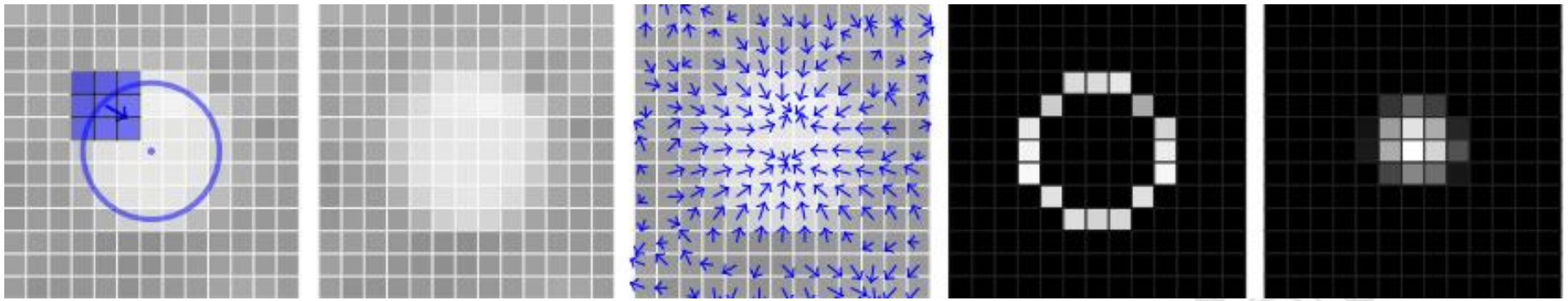


$$C = \frac{\sqrt{2}\left(\begin{pmatrix}+1 & 0 & -1\\ +2 & 0 & -2\\ +1 & 0 & -1\end{pmatrix} * I,\ \begin{pmatrix}+1 & +2 & +1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{pmatrix} * I\right)^T}{\sqrt{16\left(\begin{smallmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{smallmatrix}\right) * I^2 - \left(\left(\begin{smallmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{smallmatrix}\right) * I\right)^2 + \varepsilon^2}}$$

$$R(x,y,\alpha) = \left(\begin{pmatrix}\cos\alpha\\ \sin\alpha\end{pmatrix} \cdot C(x,y)\right)^2 = |C(x,y)|^2 \cdot \cos^2\delta$$

$$CR(x_c,y_c,r) = \frac{1}{2\pi}\int_{\alpha=0}^{2\pi} R(x_c + r\cos\alpha, y_c + r\sin\alpha, \alpha)\,d\alpha$$

Example DLR



Filtraggio con Sobel

$$C = \frac{\sqrt{2}\left(\begin{pmatrix}+1 & 0 & -1\\ +2 & 0 & -2\\ +1 & 0 & -1\end{pmatrix} * I,\ \begin{pmatrix}+1 & +2 & +1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{pmatrix} * I\right)^T}{\sqrt{16\left(\begin{smallmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{smallmatrix}\right) * I^2 - \left(\left(\begin{smallmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{smallmatrix}\right) * I\right)^2 + \varepsilon^2}}$$

Normalizzazione rispetto alla varianza locale

$$R(x,y,\alpha) = \left(\begin{pmatrix}\cos\alpha\\ \sin\alpha\end{pmatrix} \cdot C(x,y)\right)^2 = |C(x,y)|^2 \cdot \cos^2\delta$$

$$CR(x_c,y_c,r) = \frac{1}{2\pi}\int_{\alpha=0}^{2\pi} R(x_c + r\cos\alpha, y_c + r\sin\alpha, \alpha)\,d\alpha$$

Part 2

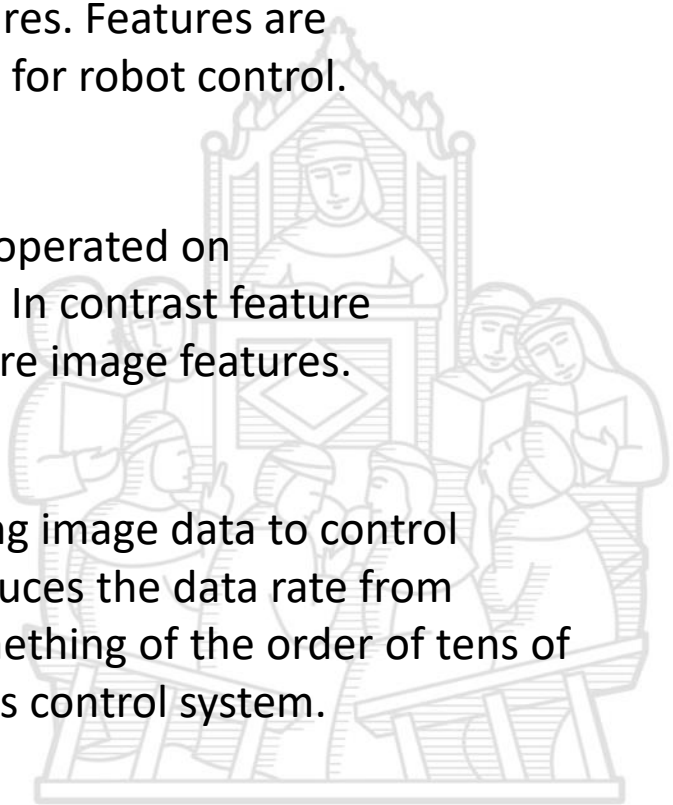
Feature extraction

Image feature extraction

We need to be able to answer pithy questions such as what is the pose of the object? what type of object is it? how fast is it moving? how fast am I moving? and so on. The answers to such questions are measurements obtained from the image and which we call image features. Features are the gist of the scene and the raw material that we need for robot control.

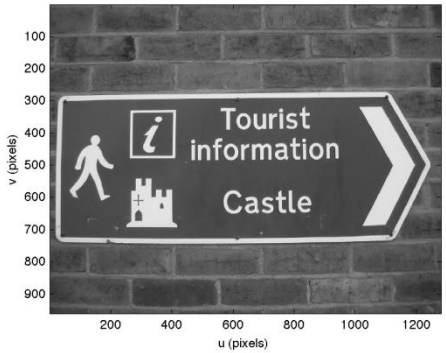
The image processing operations from the last chapter operated on one or more input images and returned another image. In contrast feature extraction operates on an image and returns one or more image features.

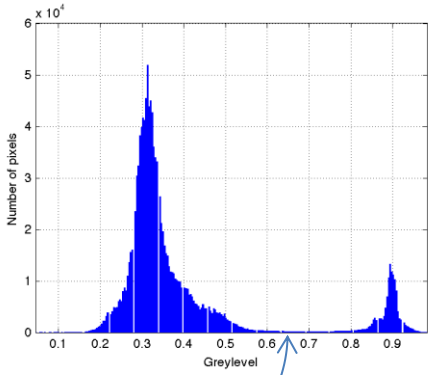
Image feature extraction is a necessary first step in using image data to control a robot. It is an information concentration step that reduces the data rate from 10 6 −10 8 bytes s –1 at the output of a camera to something of the order of tens of features per frame that can be used as input to a robot's control system.

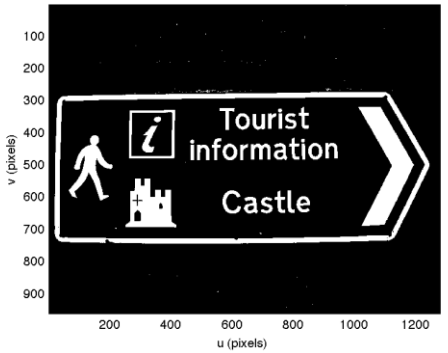


Region-features classification

Thresholding







t = 0.65

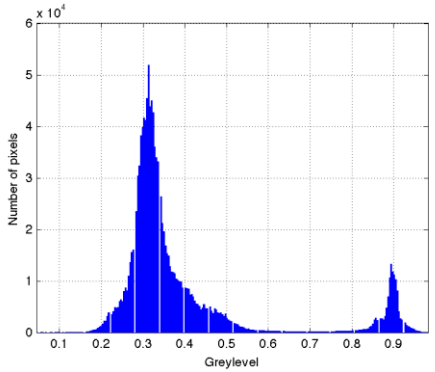
$$\boldsymbol{O}[u,v] = \begin{cases} 1, & if\ \boldsymbol{I}[u,v] > t \\ 0, & if\ \boldsymbol{I}[u,v] \leq t \end{cases}$$

How we select this value?

Otsu

Background and object can be described as classes of the image histogram

Otsu thresholding method maximize the variance between classes.



One implementation can be defined as follow:

1. Obtaining the image histogram
2. For each threshold value, $t = 0, \ldots, L-1$ the following variables should be derived
3. Compute:

$$\mu_s{}^t = \frac{\sum_{i=0}^{t} \#(i) \cdot i}{\#s}$$

$$\mu_o{}^t = \frac{\sum_{i=t+1}^{L-1} \#(i) \cdot i}{\#o}$$

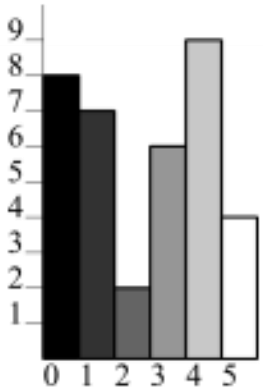
$$W_s = \frac{\#s}{\#s + \#o}$$

$$W_o = \frac{\#o}{\#s + \#o}$$

$$\sigma_b^2 = W_s W_o (\mu_s{}^t - \mu_o{}^t)^2$$

4. Maximum $\sigma^2{}_b\,(t)$ defines the correct threshold t.

Otsu



Per $t = 0$:

$$W_s = \frac{8}{36} = 0.22$$

$$\mu_s = \frac{8 \cdot 0}{8} = 0$$

$$W_o = \frac{7+2+6+9+4}{36} = \frac{28}{36} = 0.78$$

$$\mu_o = \frac{7 \cdot 1 + 2 \cdot 2 + 6 \cdot 3 + 9 \cdot 4 + 4 \cdot 5}{28} = 3.04$$

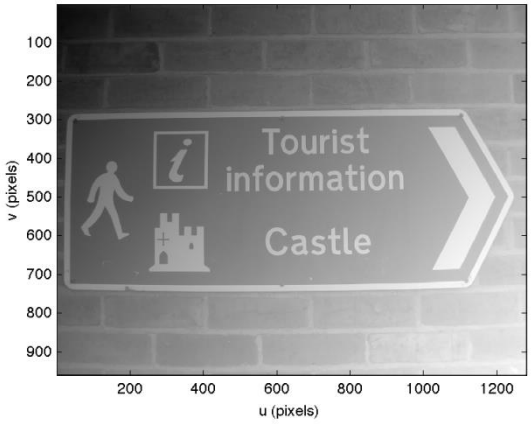
$$\sigma_b^2 = 0.22 \cdot 0.78(3.04 - 0)^2 = 1.59$$

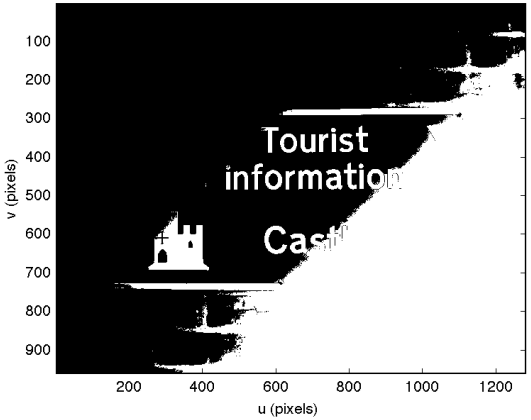
Threshold	t=0	t=1	t=2	t=3	t=4
Variance	1.59	2.56	2.63	2.14	0.87

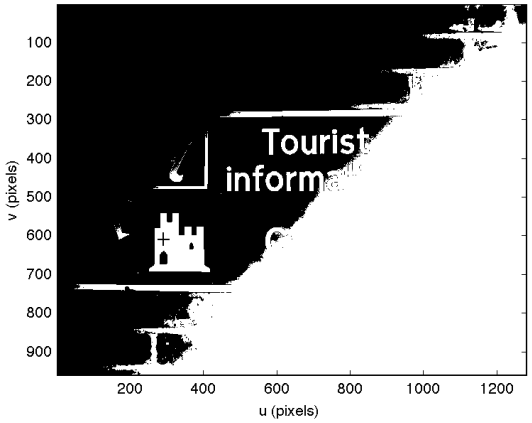
Code sample >

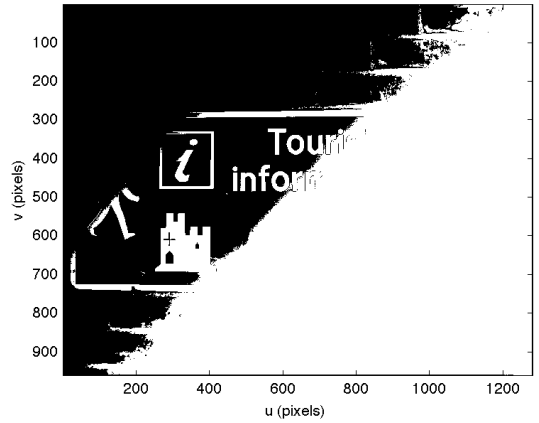
```
%OTSU
street=iread('street.png');
idisp(street);
idisp(street>t);
[rig,col]=size(street);
[n,v]=ihist(street);
plot(v,n)

max=0;
occ=n;
for t=1:256
sum_tmp=0;
sum_sf=0;
media_sf=0;
sum_ogg=0;
media_ogg=0;
peso_sf=0;
peso_ogg=0;

for i=1:t
    sum_tmp=occ(i)*i+sum_tmp;
    sum_sf=occ(i)+sum_sf;
  end

  media_sf=sum_tmp/sum_sf;
  sum_tmp=0;

  for j=t+1:256
    sum_tmp=occ(j)*j+sum_tmp;
    sum_ogg=occ(j)+sum_ogg;
  end
  media_ogg=sum_tmp/sum_ogg;

  peso_sf=sum_sf/(sum_ogg+sum_sf);
  peso_ogg=sum_ogg/(sum_ogg+sum_sf);

  var=peso_sf*peso_ogg*(media_sf-media_ogg)^2;

  if var>max
     max=var;
     soglia=t;
  end

end
```

Illumination problem



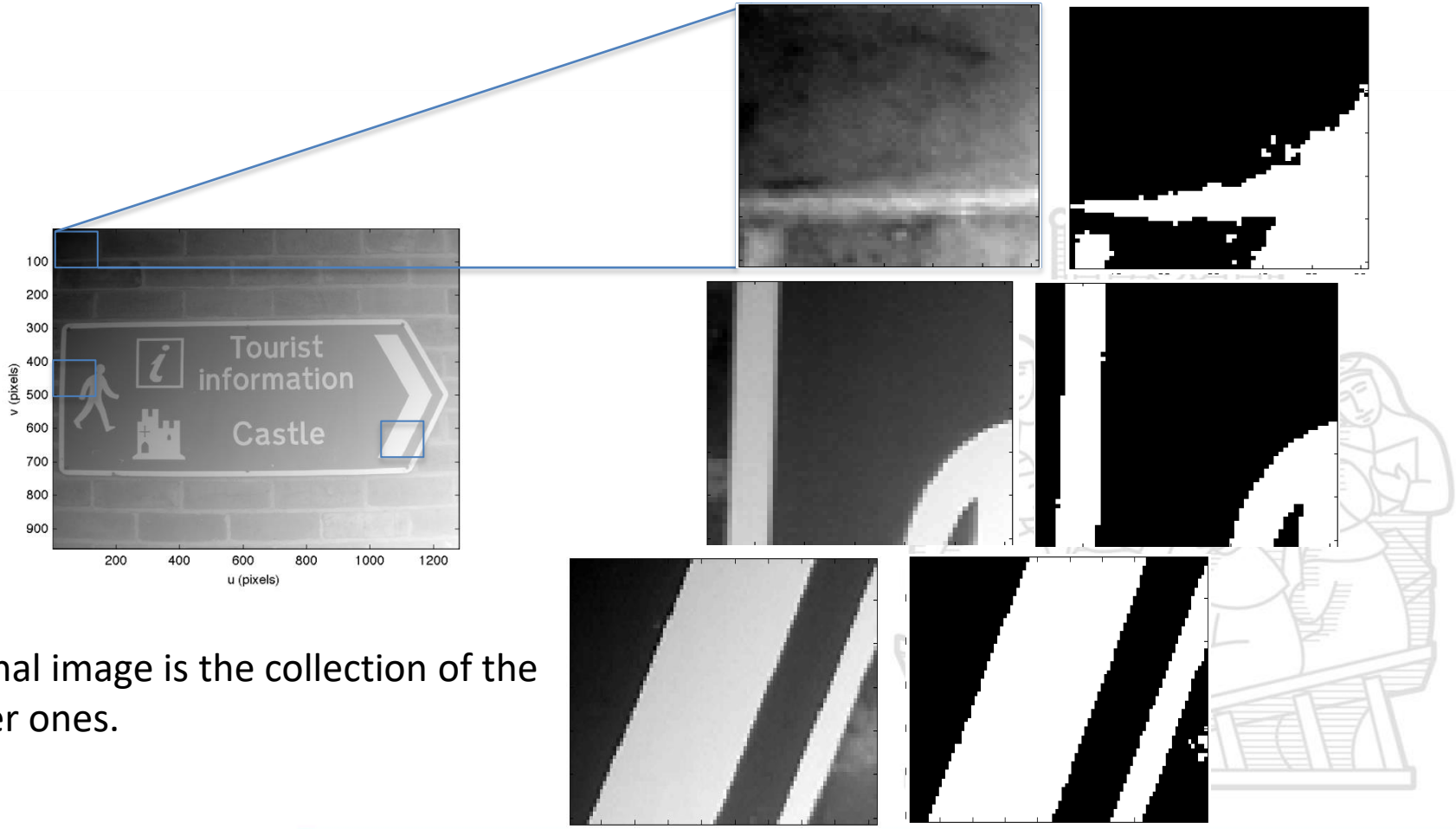






Local thresholding

We can split the image in smaller ones, and thresholding **locally** the various portions.

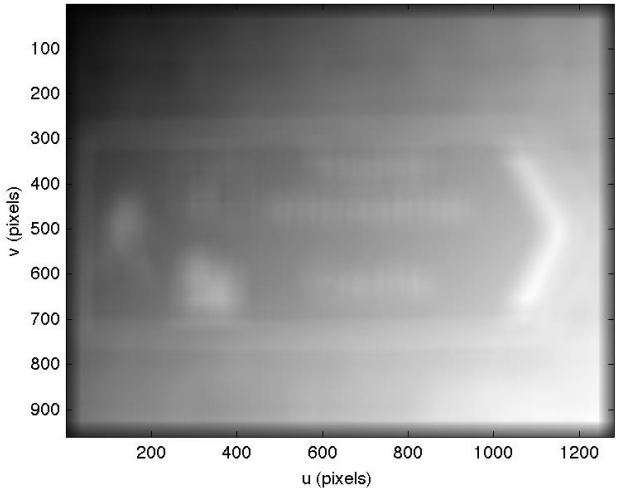


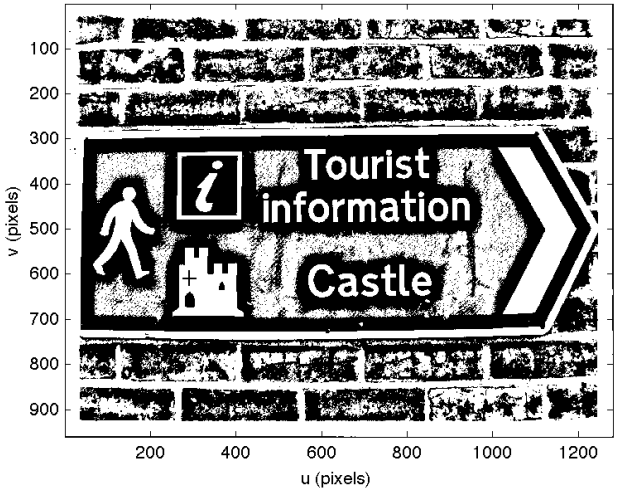
The final image is the collection of the smaller ones.

Local thresholding

Niblack algorithm used a local threshold

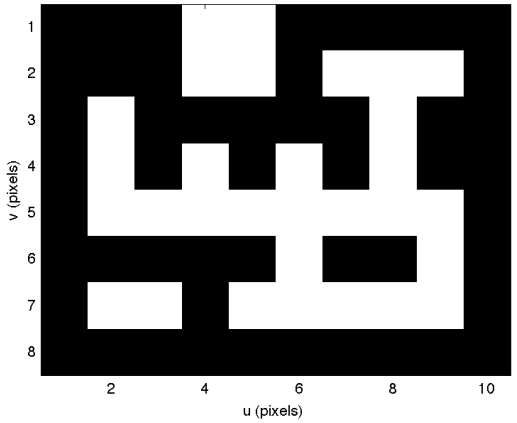
$$\boldsymbol{t}[u,v] = \mu(W) + k\sigma(W)$$

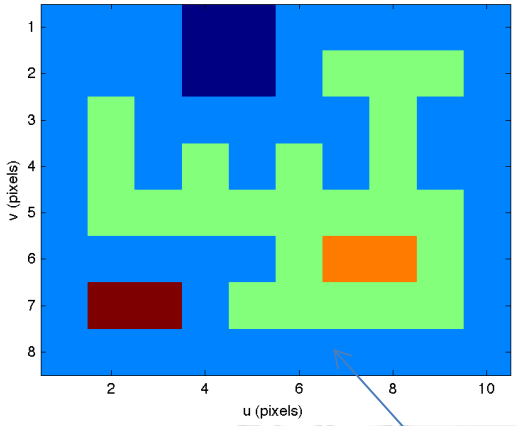




k=-2

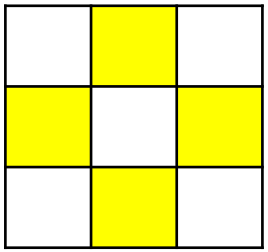
Connected components



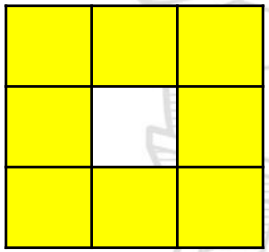


5 labels

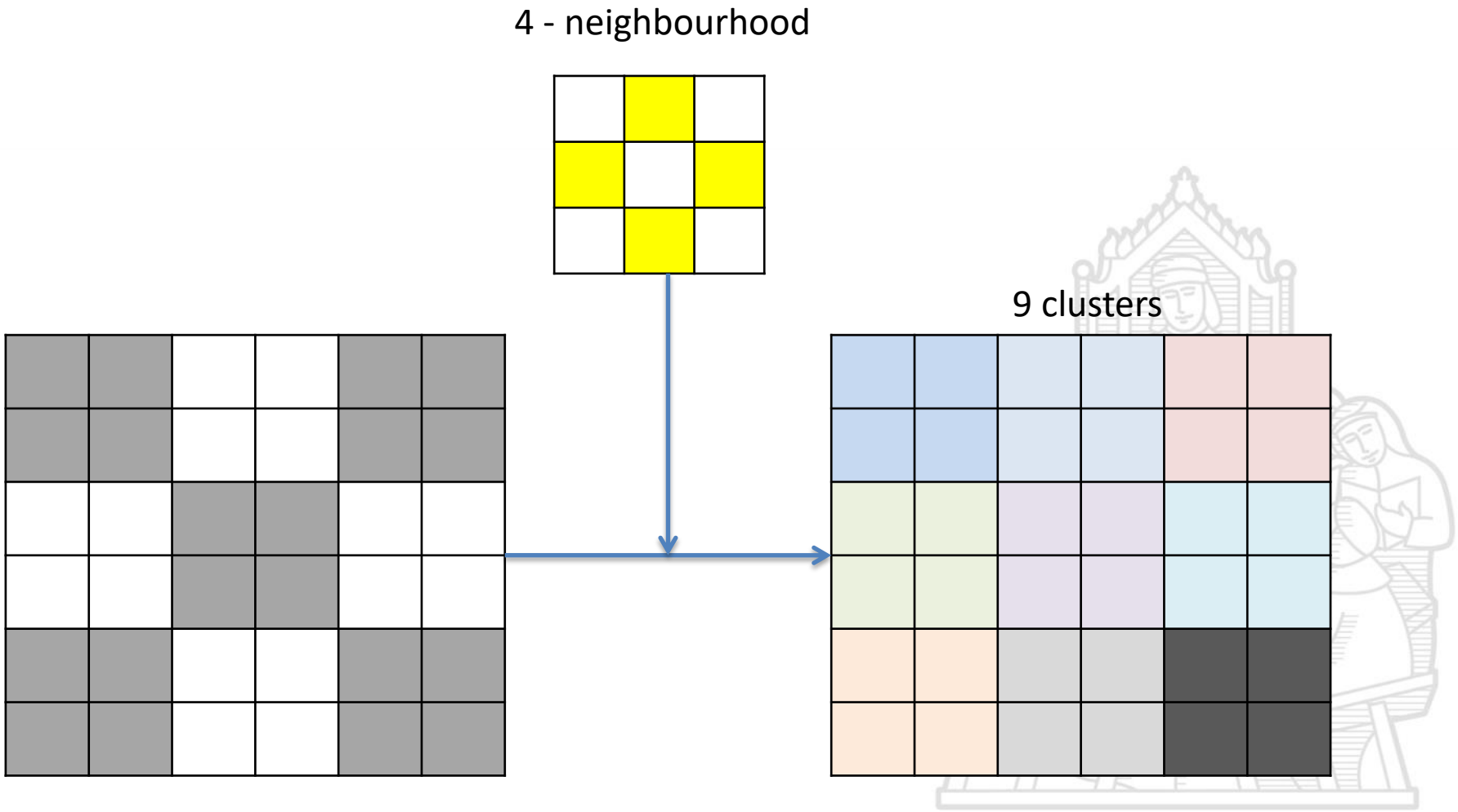
4 - neighbourhood



8 - neighbourhood

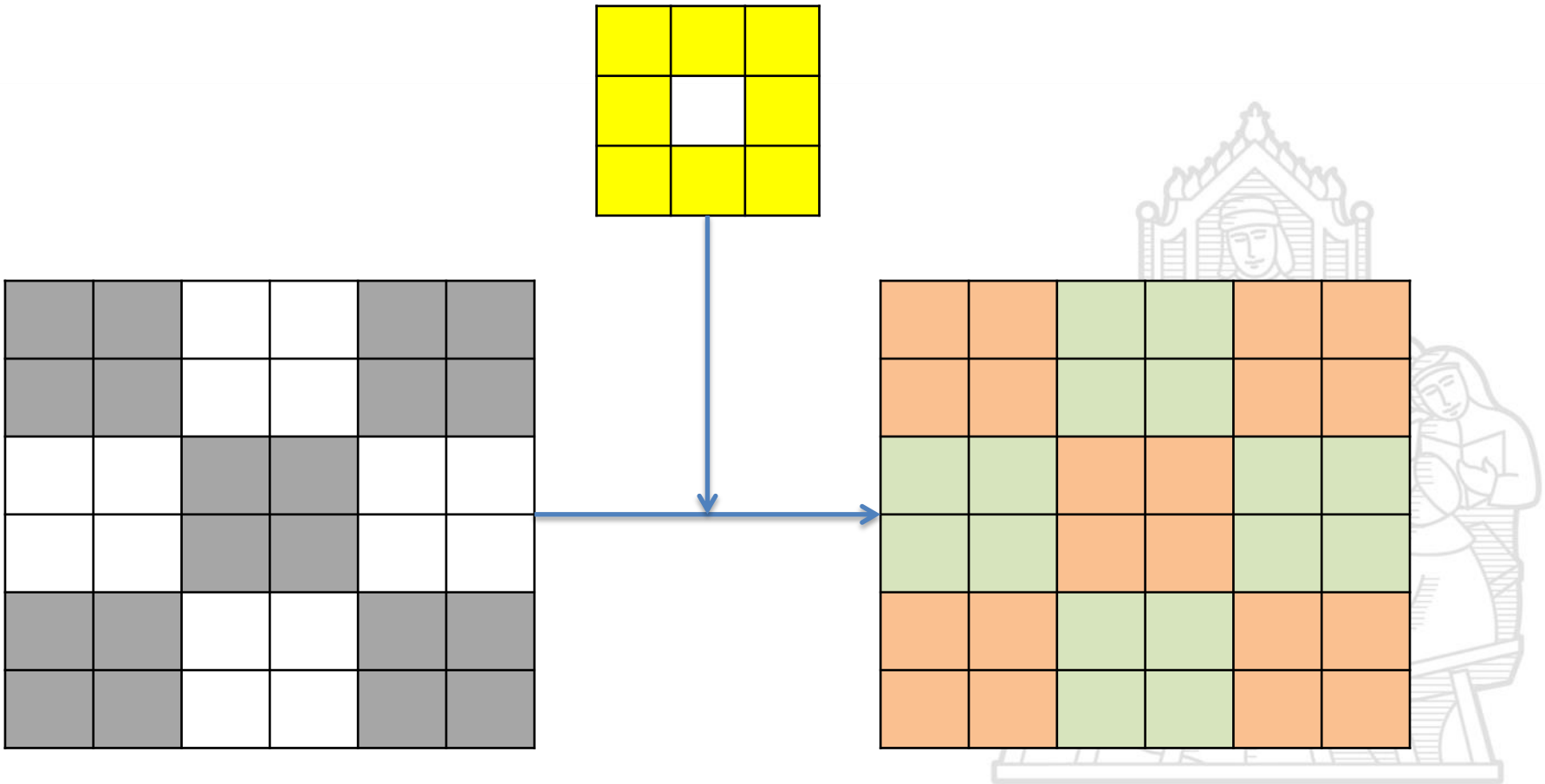


Connected components



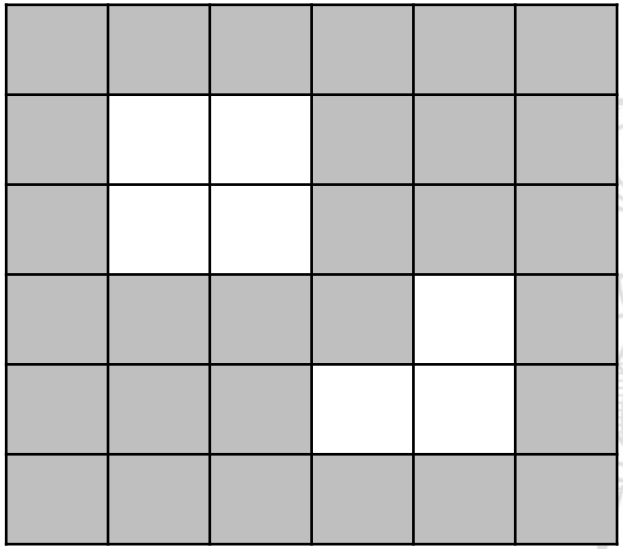
Connected components

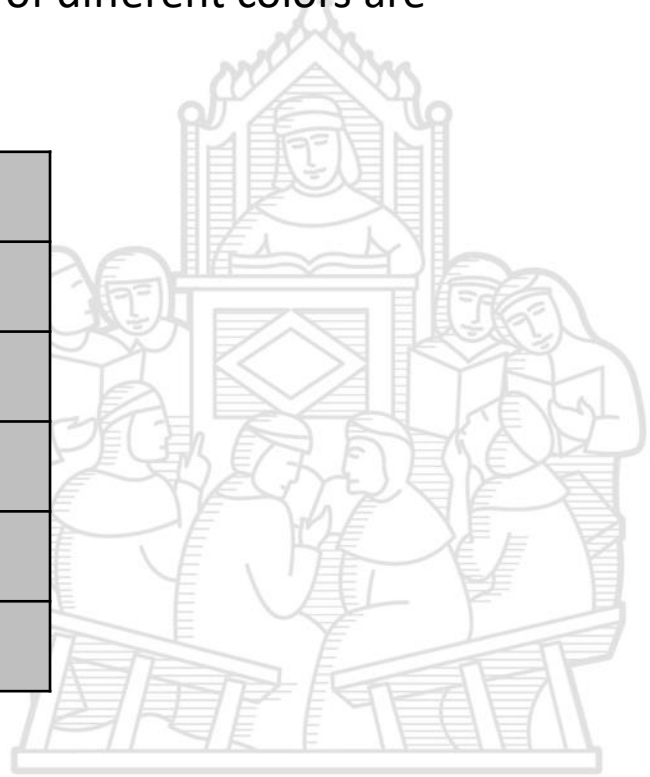
8 - neighbourhood



The motivated student algorithm

To compute the connected components of an image, we first (conceptually) split the image into horizontal runs of adjacent pixels, and then color the runs with unique labels, re-using the labels of vertically adjacent runs whenever possible. In a second phase, adjacent runs of different colors are then merged.



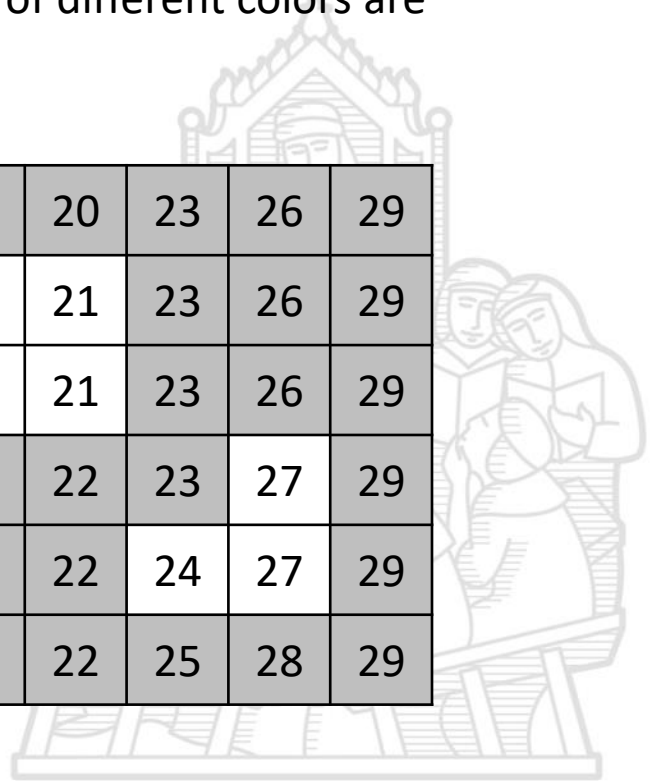


The motivated student algorithm

To compute the connected components of an image, we first (conceptually) split the image into horizontal runs of adjacent pixels, and then color the runs with unique labels, re-using the labels of vertically adjacent runs whenever possible. In a second phase, adjacent runs of different colors are then merged.

1	1	1	1	1	1
2	3	3	4	4	4
5	6	6	7	7	7
8	8	8	8	9	10
11	11	11	12	12	13
14	14	14	14	14	15

16	17	20	23	26	29
16	18	21	23	26	29
16	18	21	23	26	29
16	19	22	23	27	29
16	19	22	24	27	29
16	19	22	25	28	29



The motivated student algorithm

3 -18	6 -18	3 -21	6 -21	→	18 = 3
3 -3	**6 -3**	3 -21	6 -21	→	6 = 3
3 -3	3 -3	**3 -21**	3 -21	→	21 = 3
3 -3	3 -3	3 -3	3 -3	→	No more merges required

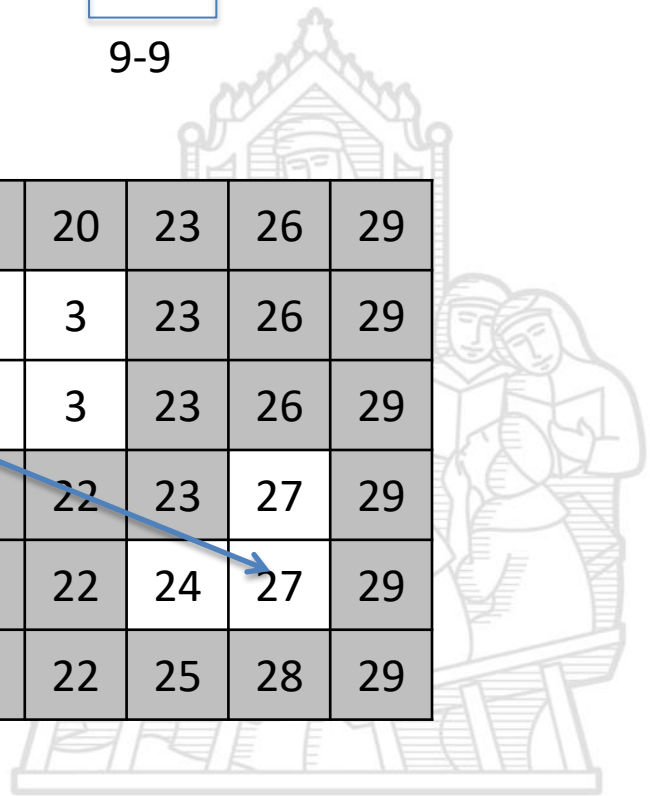
The motivated student algorithm

9-27 12-24 12-27

9-27	12-24	12-27
9-9	12-24	12-9
9-9	12-12	12-9
9-9	9-9	9-9

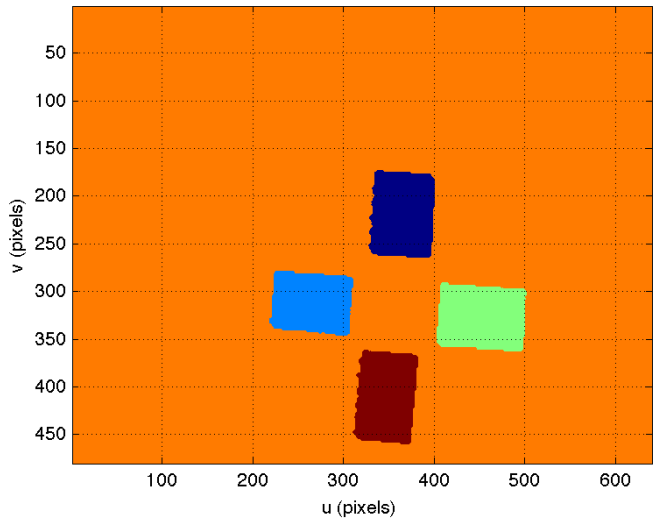
1	1	1	1	1	1
2	3	3	4	4	4
5	3	3	7	7	7
8	8	8	8	9	10
11	11	11	12	12	13
14	14	14	14	14	15

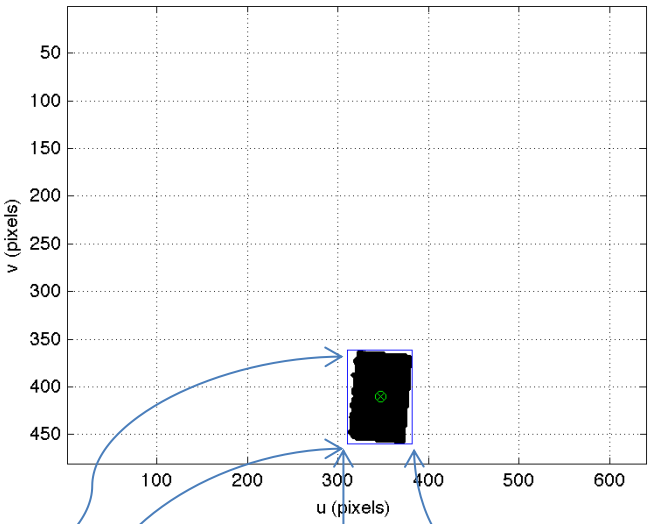
16	17	20	23	26	29
16	3	3	23	26	29
16	3	3	23	26	29
16	19	22	23	27	29
16	19	22	24	27	29
16	19	22	25	28	29



Concise description:

Bounding boxes



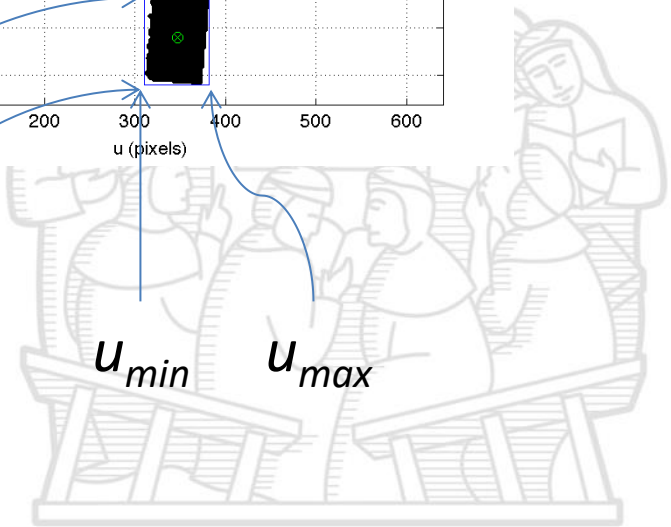


v_{max}

v_{min}

u_{min}

u_{max}



Concise description:

Moments

$$m_{pq} = \sum_{(u,v)\in \boldsymbol{I}} u^p v^q \boldsymbol{I}[u,v]$$

Where *(p+q)* is the order of the moment

$m_{00} = \sum \boldsymbol{I}[u,v]$ is the area of a region (supposing a binary image)

Centroid of the region is located in:

$$u_c = \frac{m_{10}}{m_{00}} \qquad v_c = \frac{m_{01}}{m_{00}}$$

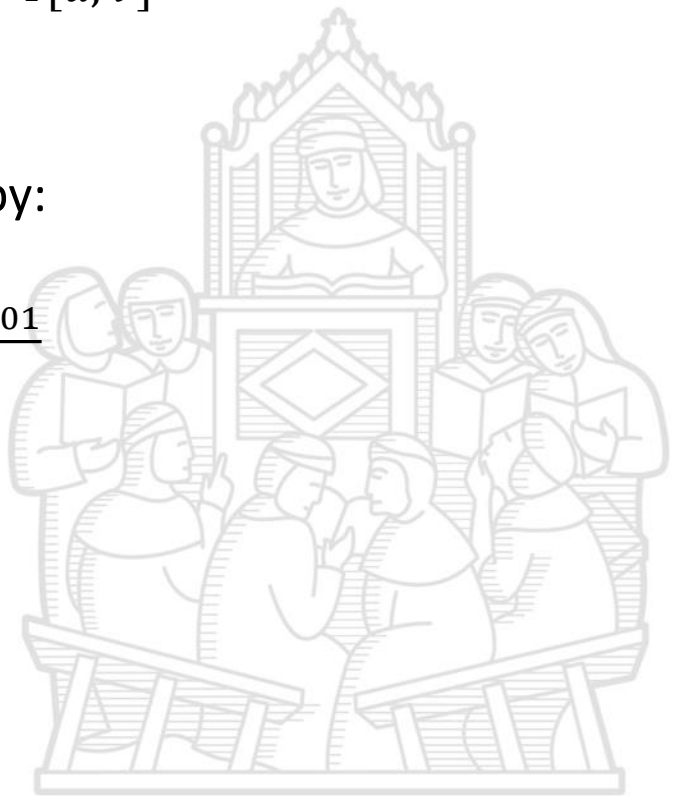
Central moments μ_{pq} are computed with respect to the centroid

$$\mu_{pq} = \sum_{(u,v)\in I} (u - u_c)^p (v - v_c)^q \boldsymbol{I}[u, v]$$

Central moments are related to moments m_{pq} by:

$$\mu_{10} = 0 \qquad \mu_{01} = 0 \qquad \mu_{11} = m_{11} - \frac{m_{10} m_{01}}{m_{00}}$$

$$\mu_{20} = m_{20} - \frac{m_{10}^2}{m_{00}} \qquad \mu_{02} = m_{02} - \frac{m_{01}^2}{m_{00}}$$



By using a thin plate analogy we can write the inertia matrix:

$$\boldsymbol{J} = \begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix}$$

About axis parallel to *u*-*v*-axes and intersecting the centroid

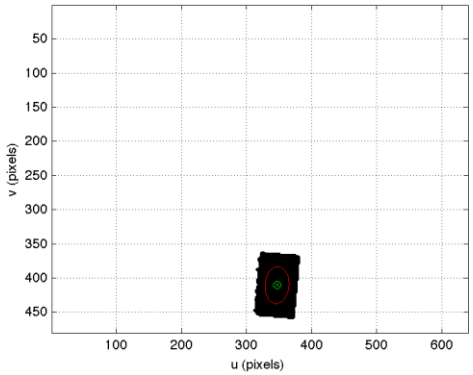
Computing eigenvalues λ_1, λ_2 , we can compute an equivalent ellipse from ***J***:

$$a = 2\sqrt{\frac{\lambda_2}{m_{00}}} \qquad b = 2\sqrt{\frac{\lambda_1}{m_{00}}}$$

Principal axis with $\lambda_2 > \lambda_1$

$$\theta = \tan^{-1}\frac{v_y}{v_x}$$ ← Eigenvectors

Orientation



Features invariance

Some region features are invariant with respect to certain transformations.

$$\frac{a}{b}$$

$$\rho = \frac{4\pi m_{00}}{p^2}$$

$$\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
\phi_6 &= (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]
\end{aligned}$$

	Translation	Rotation	Scale
Area	Y	Y	N
Centroid	N	Y	Y
Aspect ratio	Y	Y	Y
Orientation	Y	N	Y
Circularity	Y	Y	Y
Hu moments	Y	Y	Y

With normalized moments:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \gamma = \frac{1}{2}(p+q) + 1, p+q = 2, 3, \ldots$$

Line features

Hough transformation

It transforms the original image in an accumulation matrix in the parameters plane.

Every points that belong to the researched function (line, circle,. . .) increase the accumulation value.

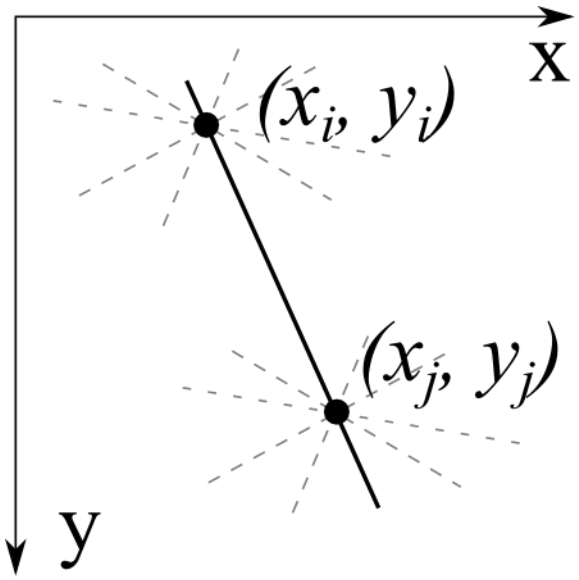
Few disadvantages

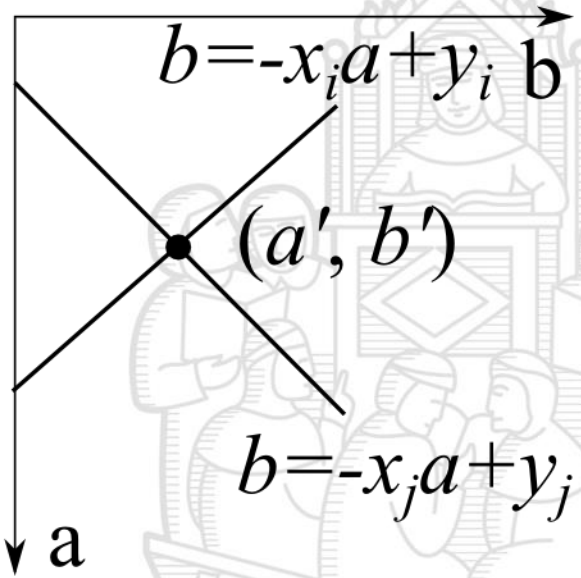
- high computational cost
- requires perfect shapes or produces several wrong detections

Line in parameters plane

$y = a \cdot x + b \rightarrow b = -x_i \cdot a + y_i$

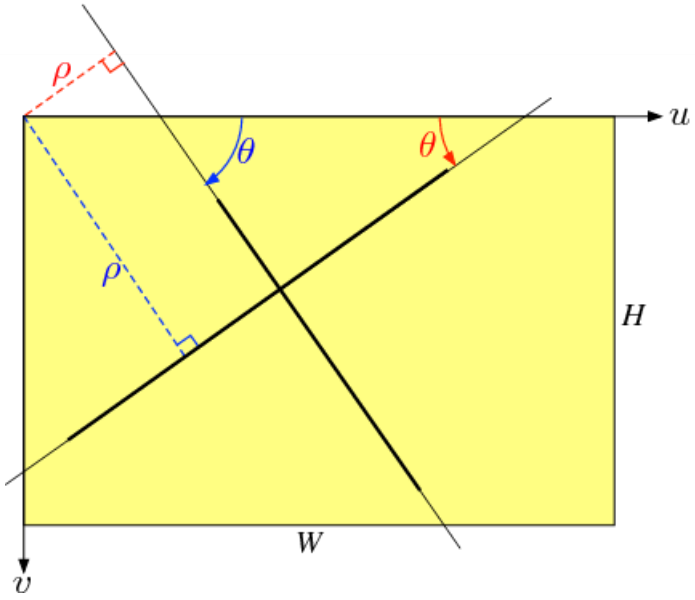
The linear function $b = -x_i \cdot a + y_i$ in the parameters plane represents all the linear functions that belong to the generic point (x_i , y_i).





Each point of the same function increase the accumulation *(a', b')*.

Polar parametrization



- The line shown can be described by the function

$$y=ax+b$$

and identified by the couple of parameters:

(a,b)=(-0.5,0.5)

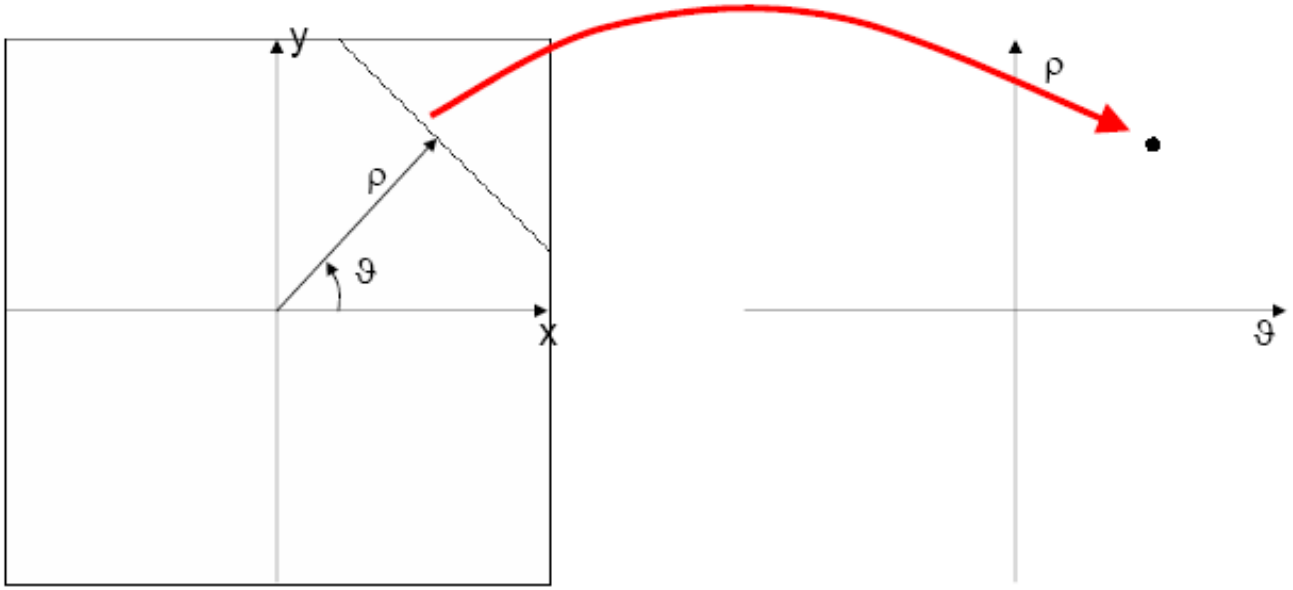
- or by the function

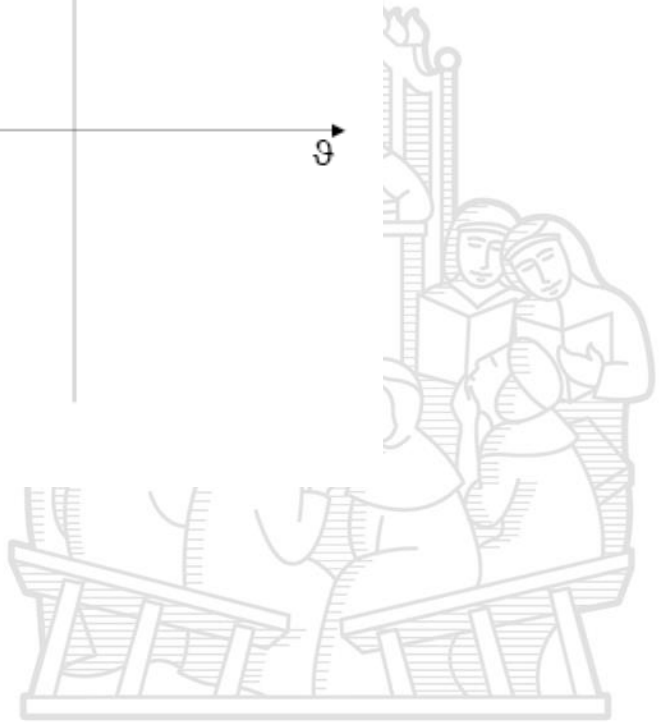
$$\rho = x \cos\vartheta + y \sin\vartheta$$

- and identified by the couple:

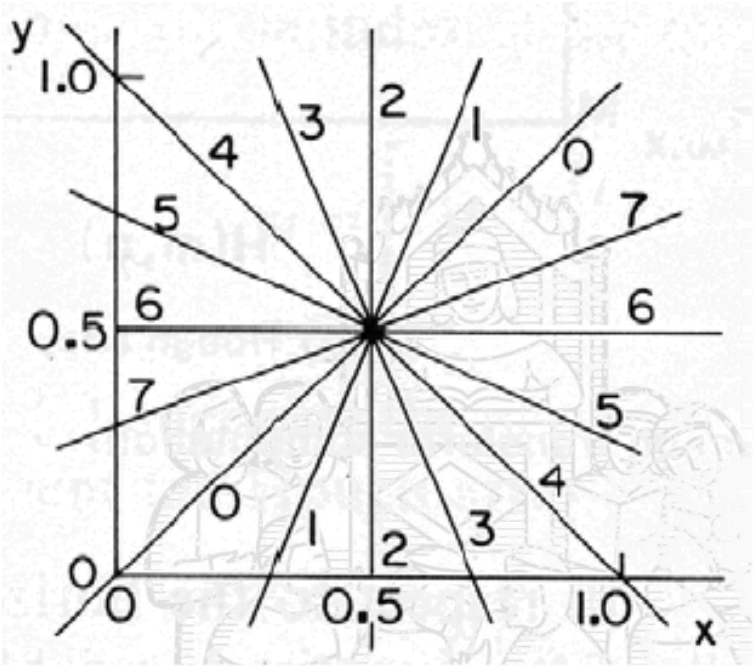
(ρ,ϑ)=(0.447,1.107)

Transformation of the plane

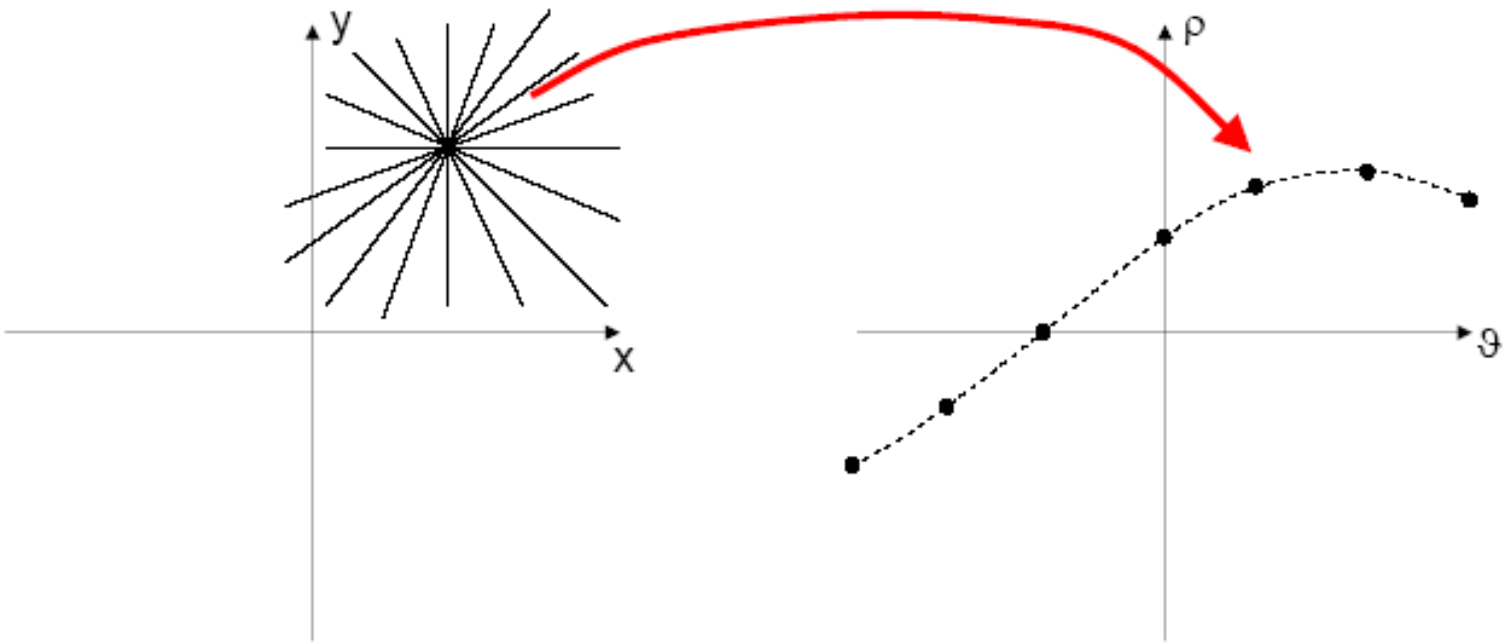




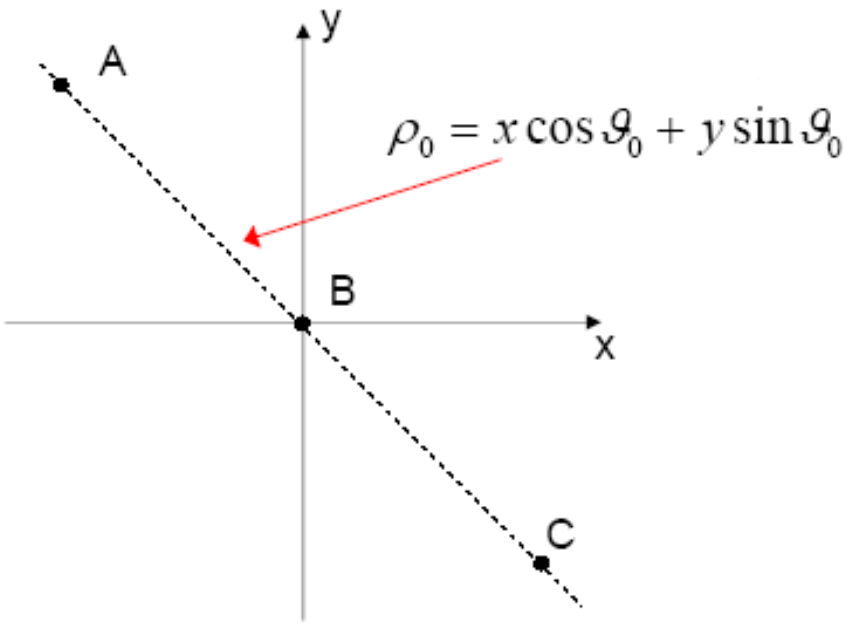
- In the image plane, one point is identified by the intersection of lines.
- Each point P corresponds, in the parameter plane, to the curve given by the image points of the lines passing through P

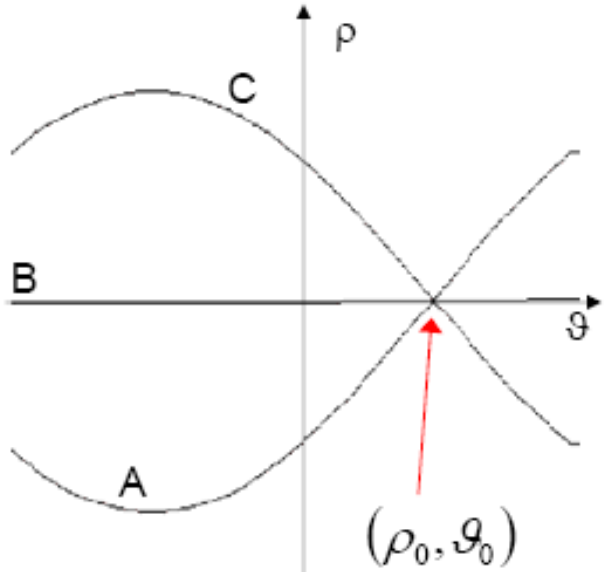


Transformation of a point



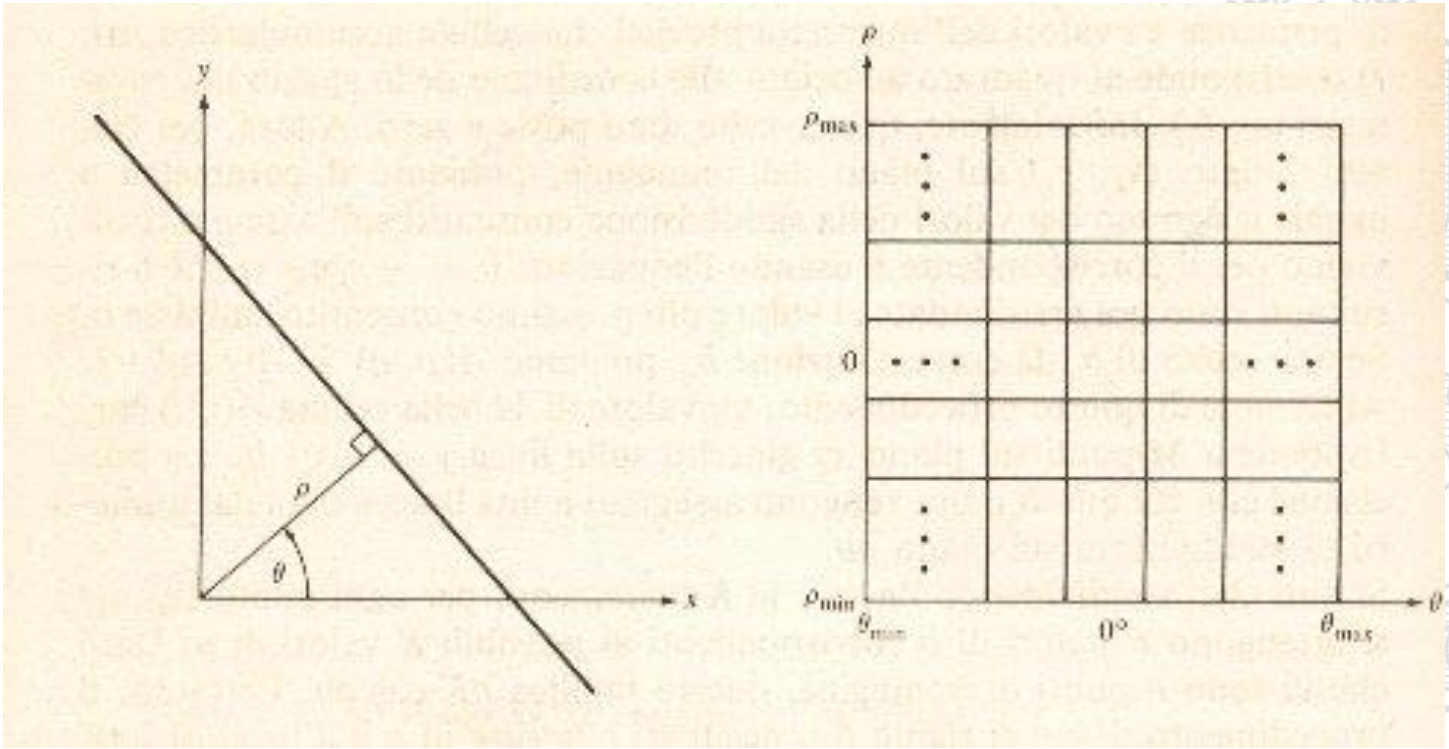
Detection of a lines on the transformed plane





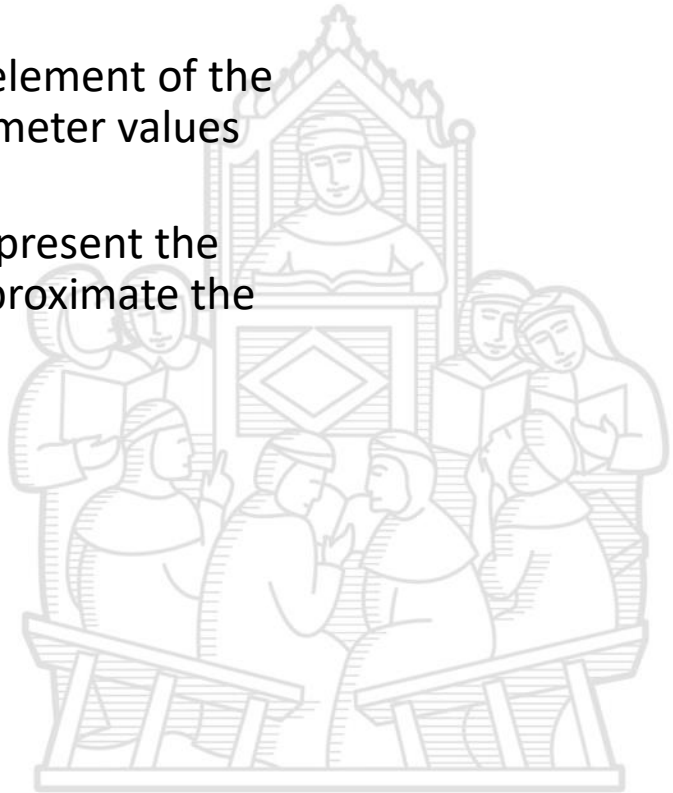
Hough's method with the polar representation of the line

$$\rho = x \cos \theta + y \sin \theta$$

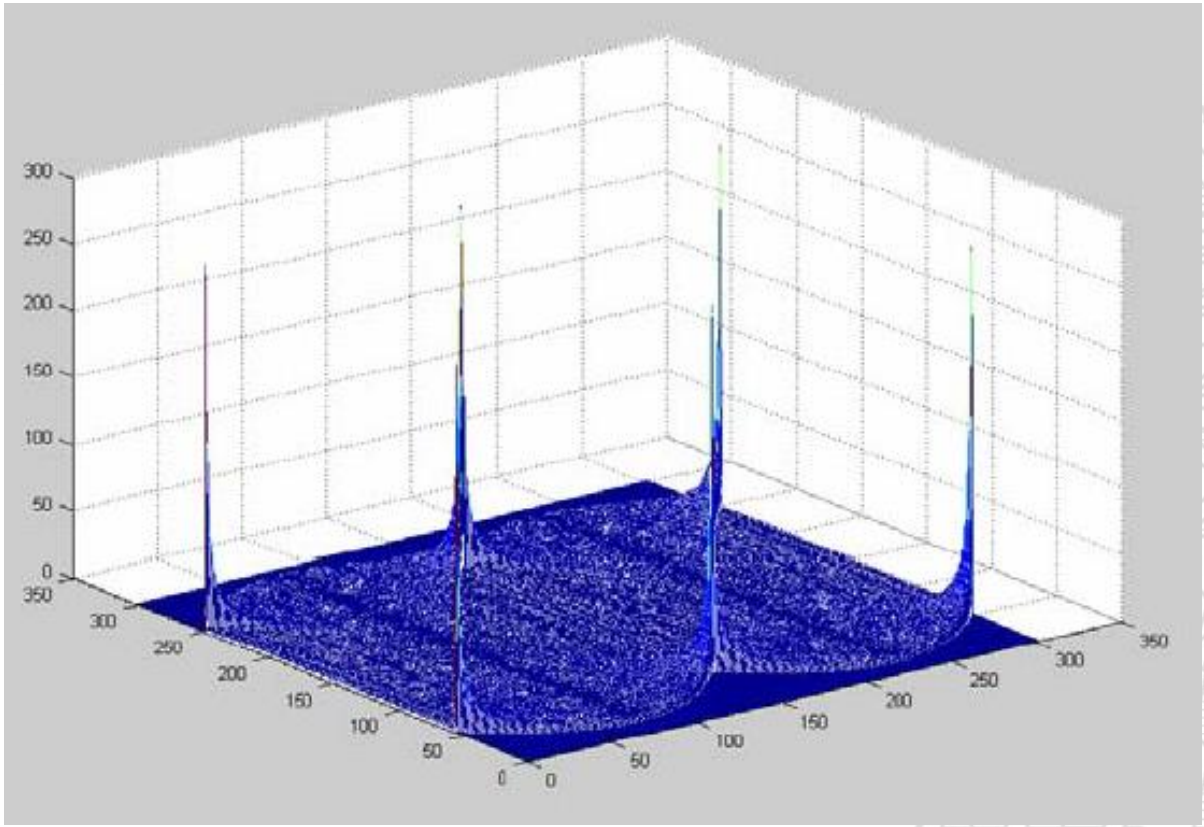


Hough's algorithm

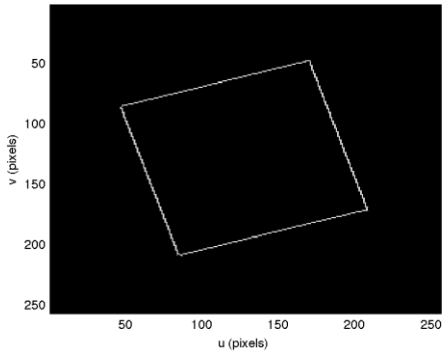
1. Quantize the parameter space between appropriate minimum and maximum values
2. Create an accumulation array with size equal to the number of parameters, initialized to 0
3. For each edge in the image, increment of the element of the accumulation array corresponding to the parameter values of the curves on which the edge lays
4. The local maxima in the accumulation array represent the parameter values of the curves that better approximate the boundary

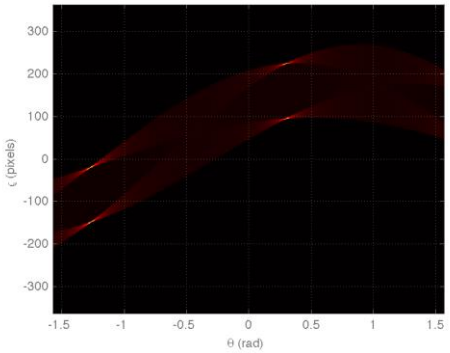


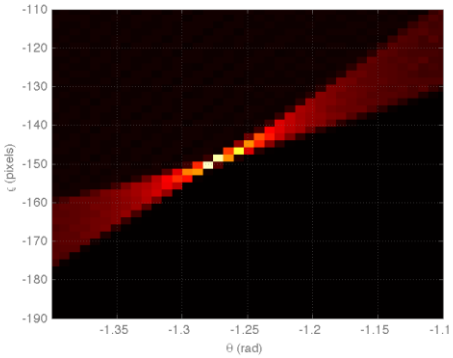
Example of accumulation matrix

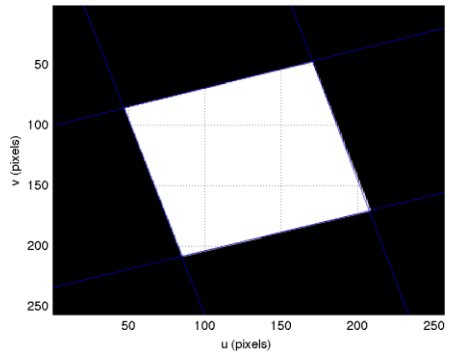


Example of the Hough's method to a rectangle

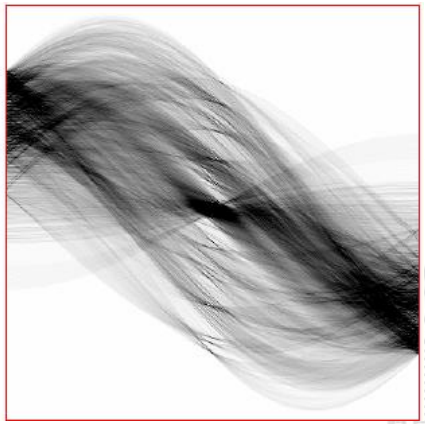




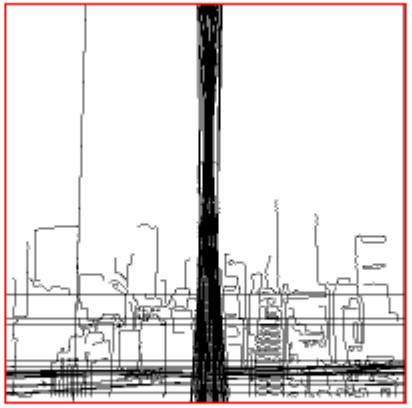




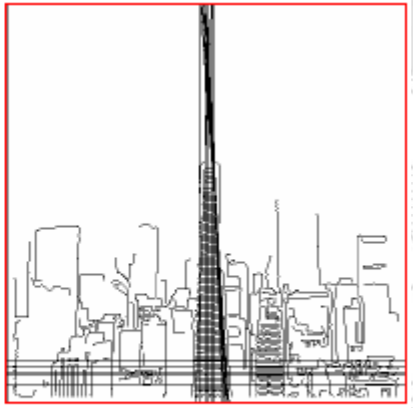
The problem of selecting the ‘right’ curves



Soglia: 101

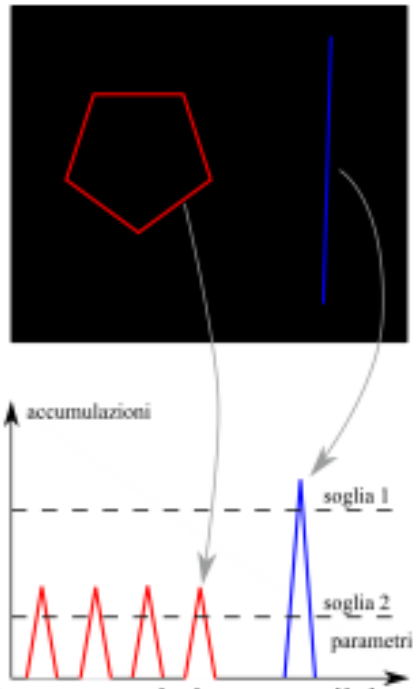


Soglia: 140



Soglia: 160

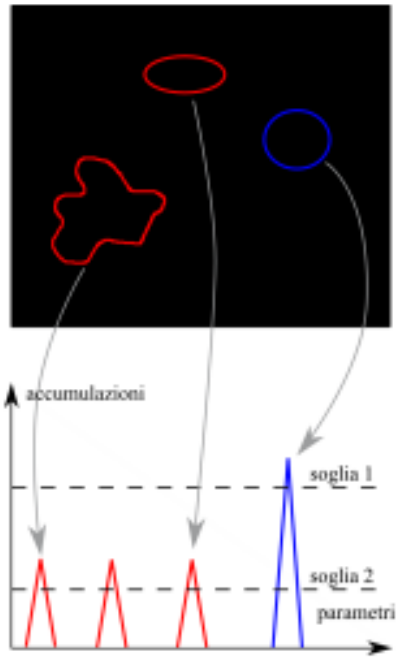
Square and lines



- depending on the length of the line, the accumulation has different values (lower or higher)
- a threshold should be selected to separate the key features from the other elements

In this case, it is possible to lower the threshold and each lines will be detected.

Ellipsis and circles



- same procedure can be used to detect circles
- in this case is difficult to identify the right threshold

Optic flow

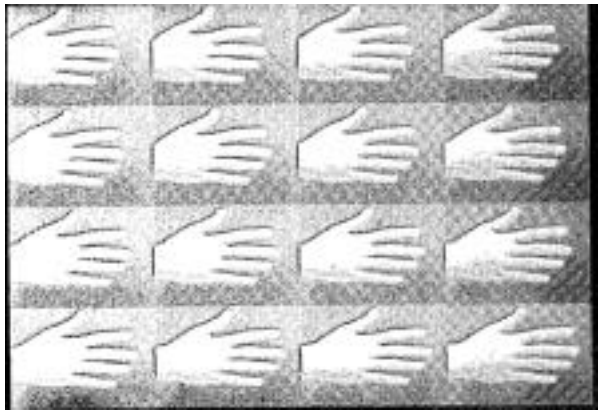
The motion is a significant part of our visual process, and it is used for several purposes:

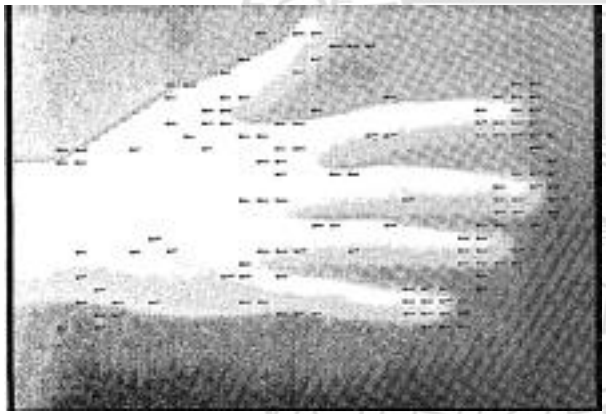
- to recognize tridimensional shapes
- to control the body by the oculomotor control
- to organize perception
- to recognize object
- to predict actions
- …

Optic flow

A surface or object moving in the space projects in the image plane a bidimensional path of speeds, *dx/dt* and *dy/dt* that is often referred to as *bidimensional motor field*.

The aim of the *optic flow* is to approximate the variation over time of the intensity levels of the image.





We consider that the intensity *I* of a pixel *(x, y)* at the instant *t*, moves to a neighbor pixel in the time *t+dt*, thus:

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \qquad (7)$$

Expanding in Taylor serie:

$$I(x + dx, y + dy, t + dt) = I(x, y, t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt$$

and taking as a reference (7) :

$$\frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt = 0$$

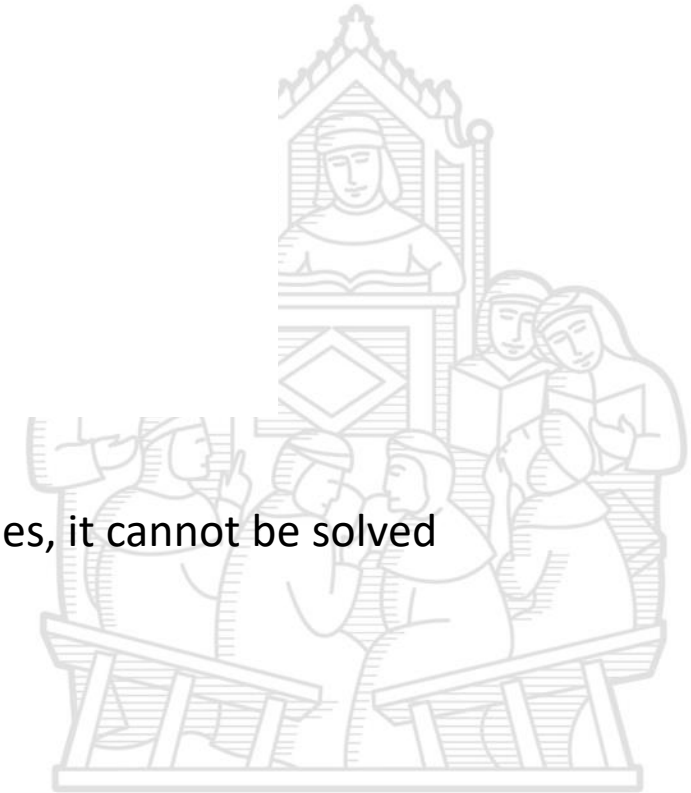
This is the *gradient constraint equation* :

$$\frac{\partial I}{\partial x}\dot{x} + \frac{\partial I}{\partial y}\dot{y} + \frac{\partial I}{\partial t} = 0$$

That can be rewritten as:

$$\nabla I \cdot V^T + \frac{\partial I}{\partial t} = 0$$

with $V=(\dot{x}, \dot{y})$



Since the gradient constraint equation has two variables, it cannot be solved directly. This is called the *aperture problem*.

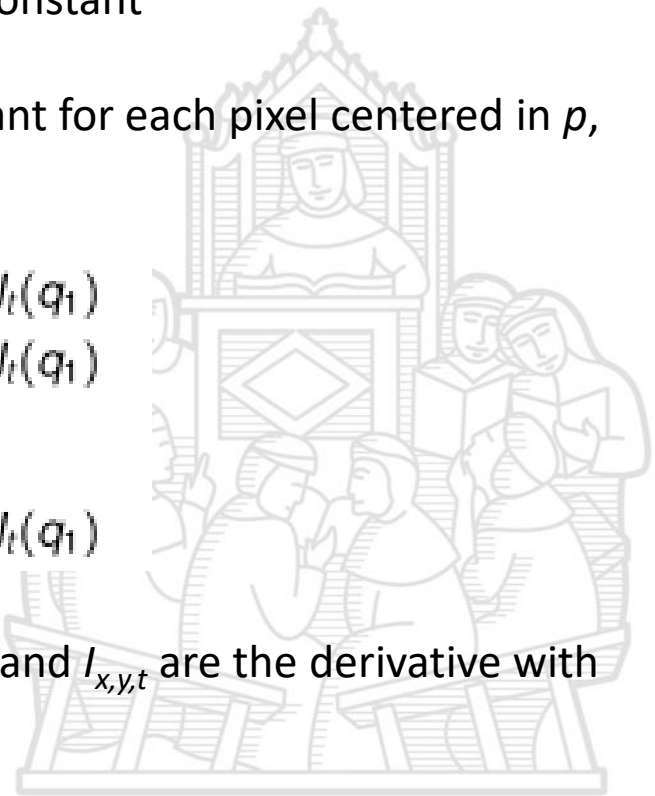
Lucas-Kanade hypothesis

To solve the aperture problem, they hypothesize:

- the motion of the intensity of pixel among two subsequent frames is small
- the motion in a small local neighbor of the pixel is constant

This is equivalent to say that the optical flow is constant for each pixel centered in *p*, thus:

$$\begin{aligned} I_x(q_1)\dot{x} + I_y(q_1)\dot{y} &= -I_t(q_1) \\ I_x(q_1)\dot{x} + I_y(q_1)\dot{y} &= -I_t(q_1) \\ &\vdots \\ I_x(q_1)\dot{x} + I_y(q_1)\dot{y} &= -I_t(q_1) \end{aligned}$$



Where $q_1, \ldots, q_n$ are pixel of the window centered in *p* and $I_{x,y,t}$ are the derivative with respect to *x,y,t*

By writing the equations in vectorial form $\boldsymbol{A \cdot v = b}$ where:

$$A = \begin{bmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{bmatrix}, v = \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}, b = \begin{bmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{bmatrix}$$

This system can be solved with the least square method:

$$v = (A^T A)^{-1} A^T b$$