



# Machine Learning

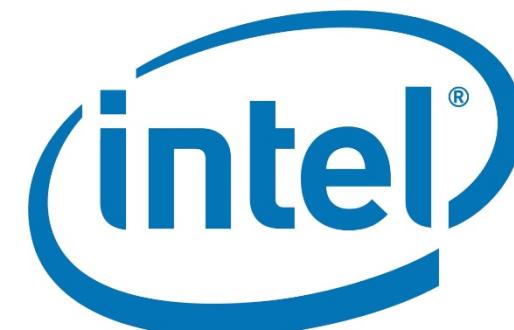
Lesson 06. Intro to OpenCV

Kirill Svyatov

Ulyanovsk State Technical University,  
Faculty of Information Systems and Technologies

# Introduction

- OpenCV is an Image Processing library created by Intel and maintained by Willow Garage.
- Available for C, C++, and Python
- Newest update is version 3.2
- Open Source and free
- Easy to use and install



# OpenCV Functionality

(More than 350 algorithms)

- Basic structures and operations
- Image Analysis
- Structural Analysis
- Object Recognition
- Motion Analysis and Object Tracking
- 3D Reconstruction



# Basic structures and operations



# Image TYPES

- The TYPE is a very important aspect of OpenCV
- Represented as CV\_<Datatype> <Number of Channels>
- Example Datatypes/ Depths

OpenCV Tag	Representation	OpenCV Value
CV_8U	8 bit unsigned integer	0
CV_8S	8 bit signed integer	1
CV_16U	16 bit unsigned integer	2
CV_16S	16 bit signed integer	3
CV_32S	32 bit signed integer	4
CV_32F	32 bit floating point number	5
CV_64F	64 bit floating point number	6

**CV\_64F contain more information but hold more RAM!**  
**In ML often have to use CV\_8U format**

# Basic Structures and Operations

- Multidimensional array operations
- Dynamic structures operations
- Drawing primitives
- Utility functions

## Victor Eruhimov:

Multidimensional array operations include operations on images, matrices and histograms. In the future, when I talk about image operations, keep in mind that all operations are applicable to matrices and histograms as well. Dynamic structures operations concern all vector data storages. They will be discussed in detail in the Technical Section. Drawing primitives allows not only to draw primitives but to use the algorithms for pixel access. Utility functions, in particular, contain fast implementations of useful math functions.



# Converting colorspaces

Function cvtColor( image, image, code)

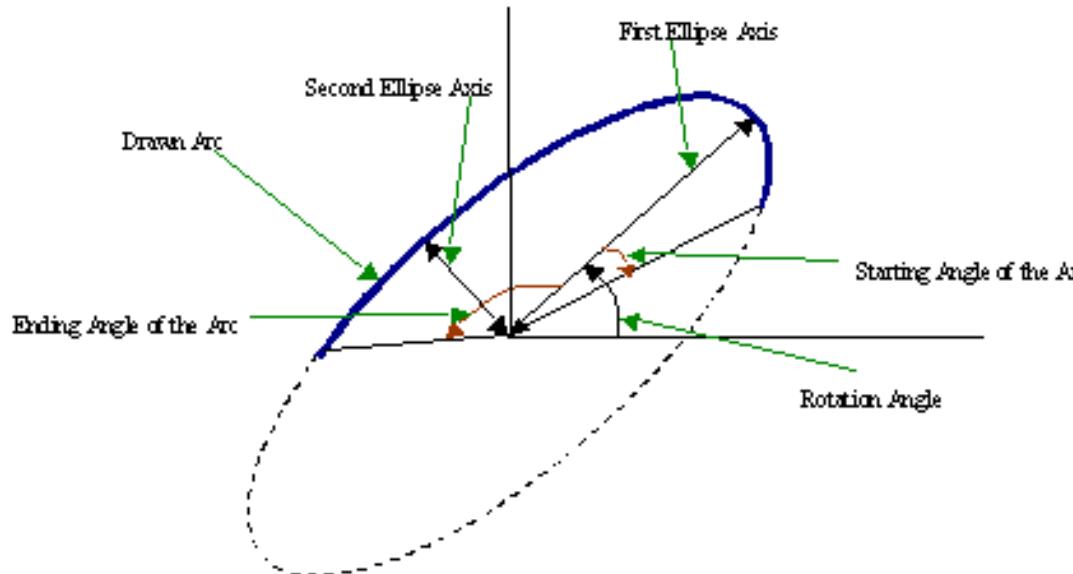
- Codes:

- **CV\_BGR2GRAY**
- **CV\_BGR2HSV**
- **CV\_BGR2LUV**



# Drawing ellipse example

Draws a simple or thick elliptic arc or fills an ellipse sector.



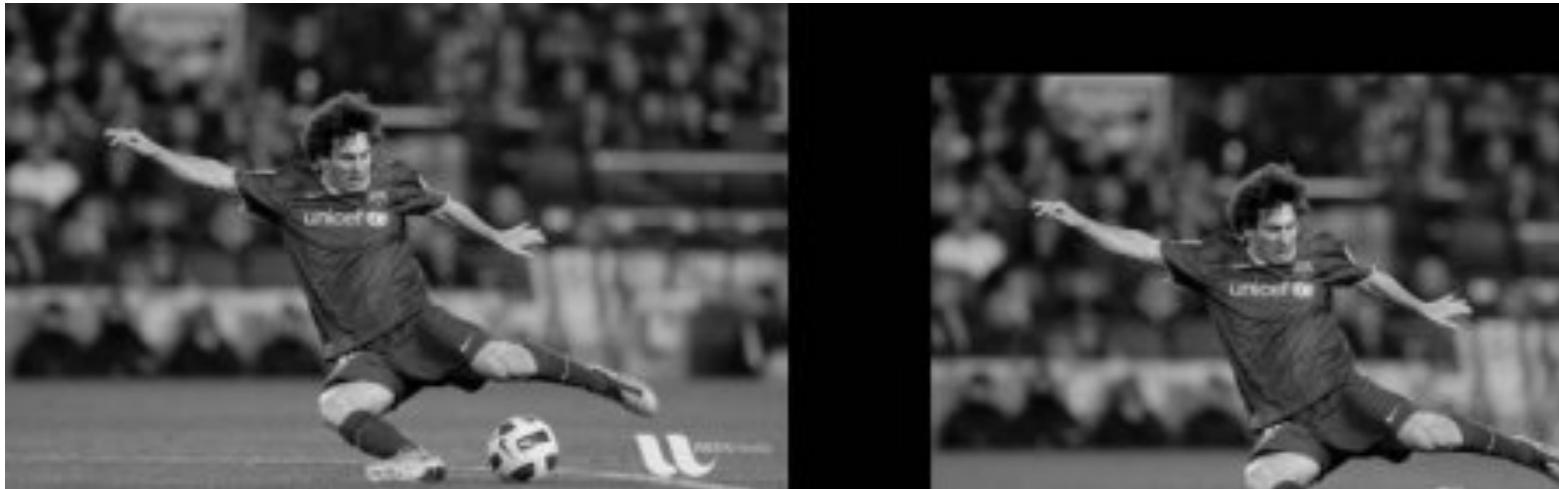
## Parameters:

- **img** – Image.
- **center** – Center of the ellipse.
- **axes** – Half of the size of the ellipse main axes.
- **angle** – Ellipse rotation angle in degrees.
- **startAngle** – Starting angle of the elliptic arc in degrees.
- **endAngle** – Ending angle of the elliptic arc in degrees.
- **color** – Ellipse color.
- **thickness** – Thickness of the ellipse arc outline, if positive. Otherwise, this indicates that a filled ellipse sector is to be drawn.
- **etc...**

# Transformations: Translation

Translation is the shifting of object's location:

```
img = cv2.imread('messi5.jpg',0)
rows,cols = img.shape
M = np.float32([[1,0,100],[0,1,50]])
dst = cv2.warpAffine(img,M,(cols,rows))
```



**Remember** width = number of columns, and height = number of rows

# Transformations: Rotation

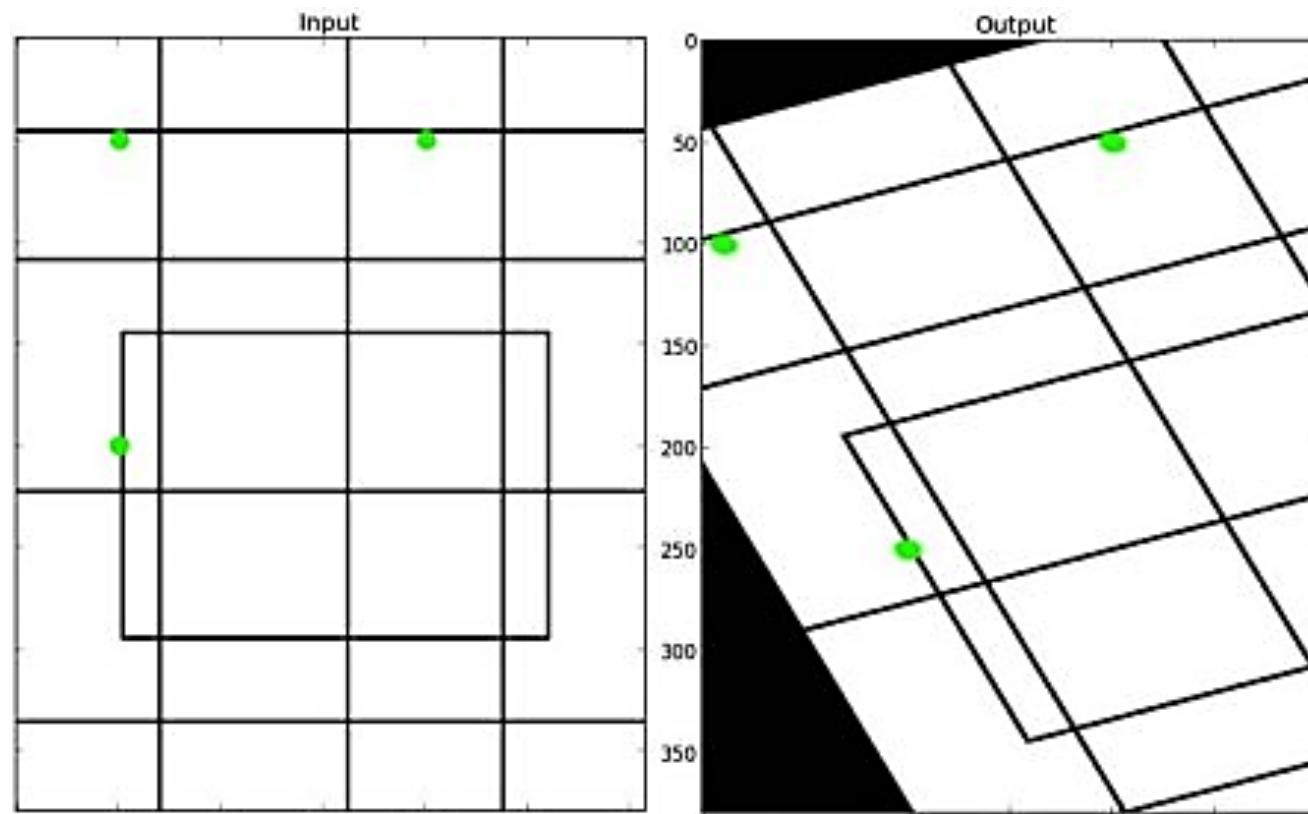
Rotation of an image for an angle  $\theta$  is achieved by the transformation matrix of the form  
To find this transformation matrix, OpenCV provides a function, **cv2.getRotationMatrix2D** :

```
img = cv2.imread('messi5.jpg',0)
rows,cols = img.shape
M = cv2.getRotationMatrix2D((cols/2,rows/2),90,1)
dst = cv2.warpAffine(img,M,(cols,rows))
```



# Transformations: Affine Transformation

In affine transformation, all parallel lines in the original image will still be parallel in the output image. To find the transformation matrix, we need three points from input image and their corresponding locations in output image:



# Transformations: Affine Transformation code

```
img = cv2.imread('drawing.png')
rows,cols,ch = img.shape

pts1 = np.float32([[50,50],[200,50],[50,200]])
pts2 = np.float32([[10,100],[200,50],[100,250]])
M = cv2.getAffineTransform(pts1,pts2)
dst = cv2.warpAffine(img,M,(cols,rows))

plt.subplot(121),plt.imshow(img),plt.title('Input')
plt.subplot(122),plt.imshow(dst),plt.title('Output')
plt.show()
```



# Transformations: Downsampling resize

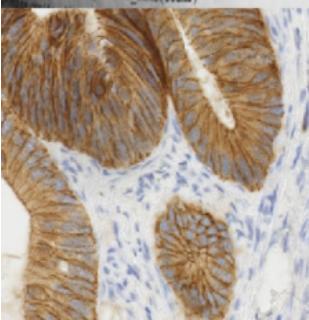
origin 400x400



Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```



area 50x50



Region-based segmentation

As in the previous markers of the two extreme values. These markers are continuous on an ROI response to either object or background. Then, the markers are used to segment the ROI.

```
>>> markers = np.zeros_like(coins)
```



nearest 50x50



Region-based segmentation

In this case the markers of the two extreme values. These markers are continuous on an ROI response to either object or background. Then, the markers are used to segment the ROI.

```
>>> markers = np.zeros_like(coins)
```



linear 50x50



Region-based segmentation

In this case the markers of the two extreme values. These markers are continuous on an ROI response to either object or background. Then, the markers are used to segment the ROI.

```
>>> markers = np.zeros_like(coins)
```



cubic 50x50



Region-based segmentation

In this case the markers of the two extreme values. These markers are continuous on an ROI response to either object or background. Then, the markers are used to segment the ROI.

```
>>> markers = np.zeros_like(coins)
```



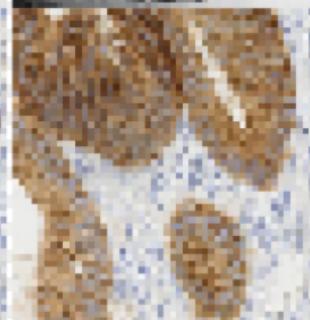
lanczos 50x50



Region-based segmentation

In this case the markers of the two extreme values. These markers are continuous on an ROI response to either object or background. Then, the markers are used to segment the ROI.

```
>>> markers = np.zeros_like(coins)
```



# Transformations: resize in code

**Very simple:**

```
W = target_width  
H = , target_height
```

```
result_image = cv2.resize(source_im, (W, H), interpolation=cv2.INTER_AREA)
```

# Image Analysis

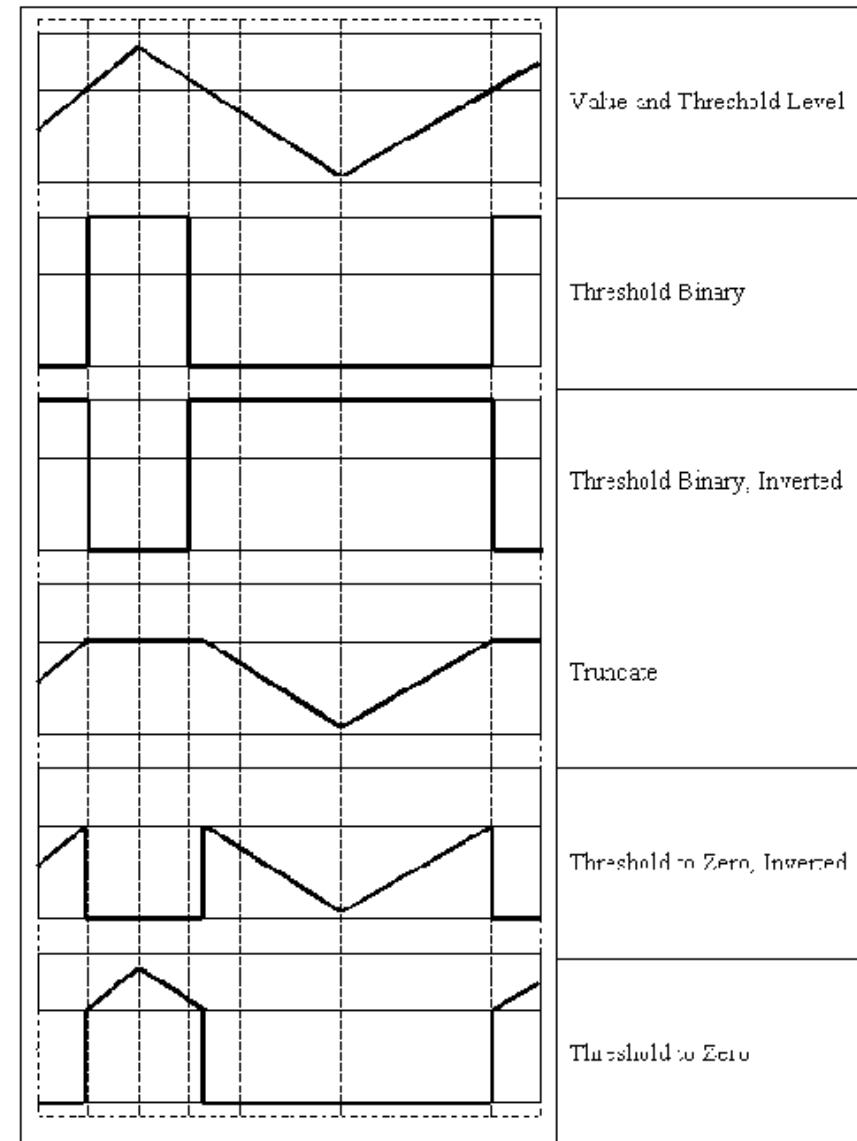


- Thresholds
- Statistics
- Pyramids
- Morphology
- Distance transform
- Flood fill
- Feature detection
- Contours retrieving



# Image Thresholding

- Fixed threshold;
- Adaptive threshold;



# Image Thresholding Examples

Original Image



Global Thresholding ( $v = 127$ )



Adaptive Mean Thresholding

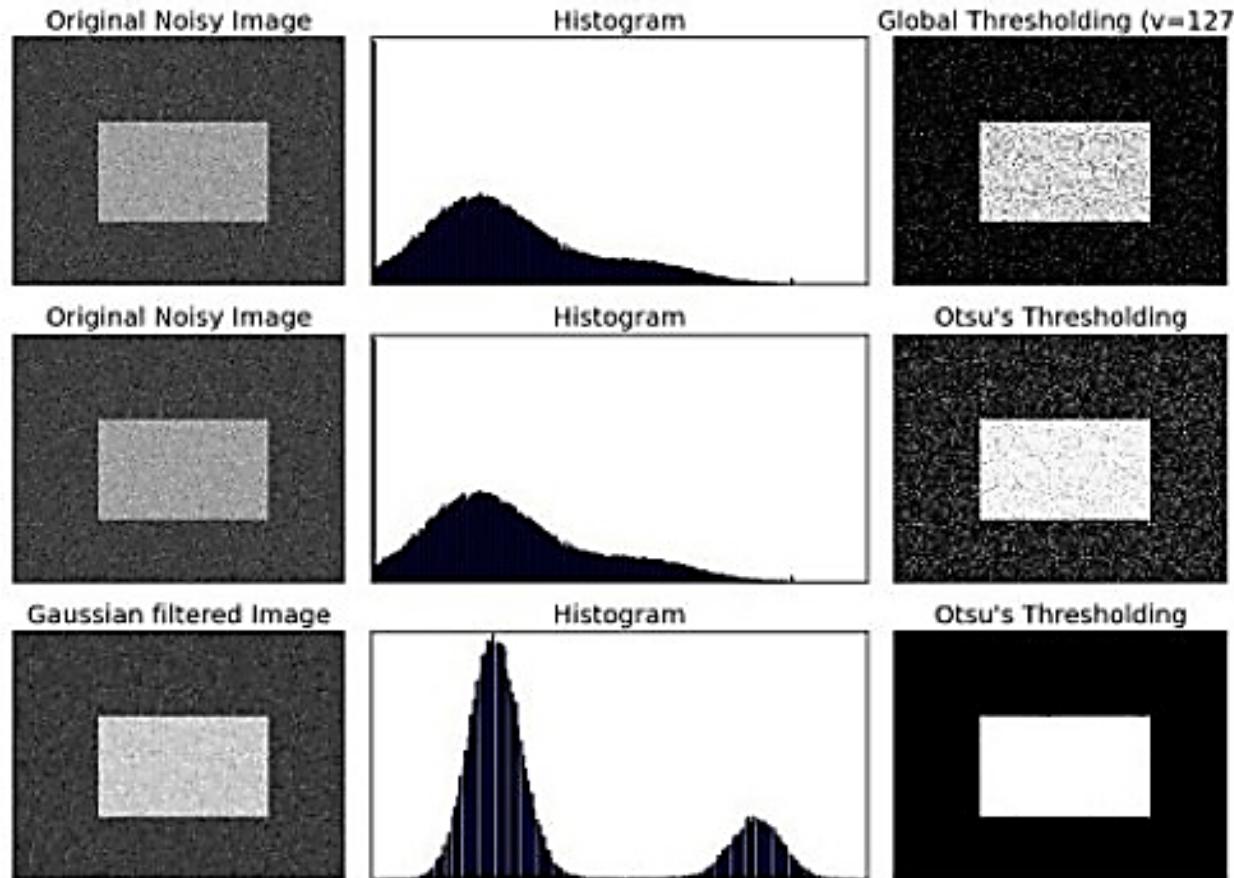


Adaptive Gaussian Thresholding



# Image Thresholding for denoising Examples

(Use Otsu's Binarization)



# Statistics

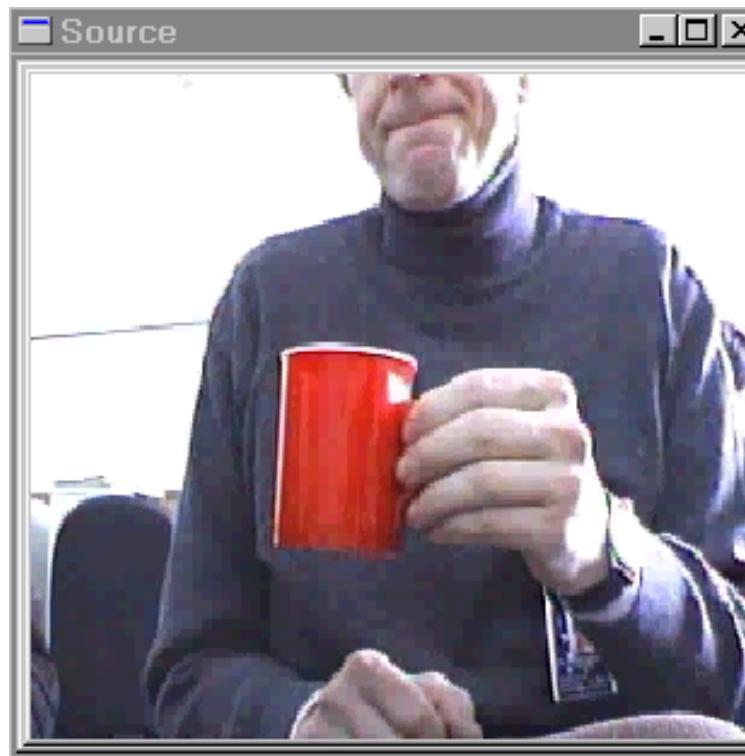
- min, max, mean value, standard deviation over the image
- Norms C, L1, L2
- Multidimensional histograms
- Spatial moments up to order 3 (central, normalized, Hu)

**Victor Eruhimov:**

In addition to simple norm calculation, there is a function that finds the norm of the difference between two images.

# Pyramid-based color segmentation

**On still pictures**



**And on movies**

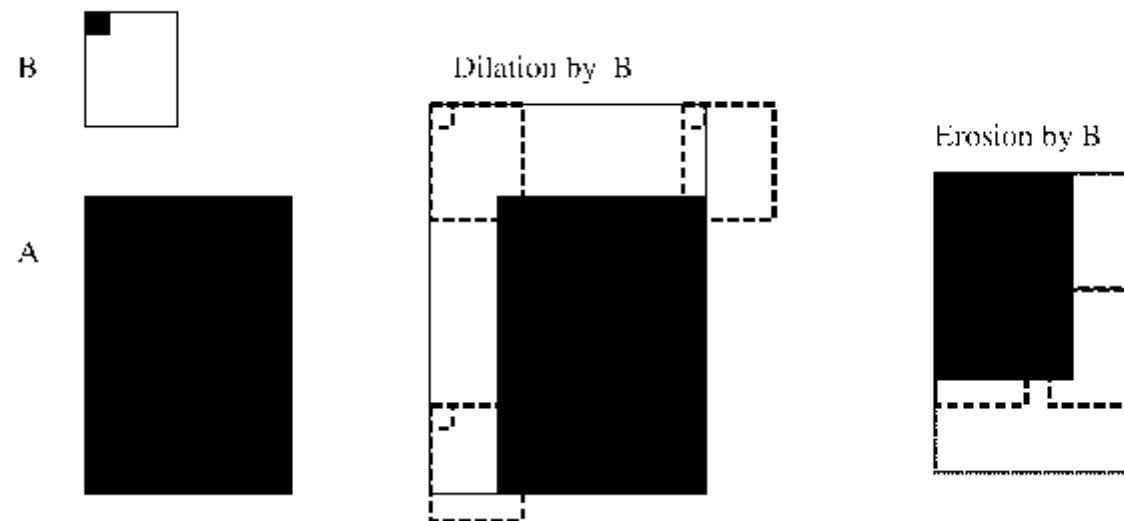


# Morphological Operations

- Two basic morphology operations using structuring element:
  - erosion
  - dilation
- More complex morphology operations:
  - opening
  - closing
  - morphological gradient
  - top hat
  - black hat

# What is Structuring Element?

- The rectangle mask with given position of a principal pixel:



# Morphological Operations Examples

Morphology - applying Min-Max. Filters and its combinations:

Image I



Erosion  $I \ominus B$



Dilatation  $I \oplus B$



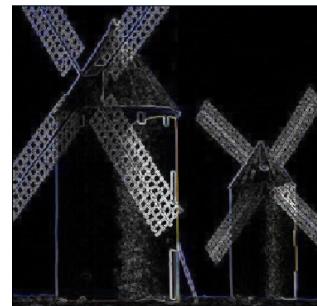
Opening  $I \circ B = (I \ominus B) \oplus B$



Closing  $I \bullet B = (I \oplus B) \ominus B$



Grad( $I$ ) =  $(I \oplus B) - (I \ominus B)$



TopHat( $I$ ) =  $I - (I \ominus B)$



BlackHat( $I$ ) =  $(I \oplus B) - I$



# Distance Transform

- Calculate the distance for all non-feature points to the closest feature point
- Two-pass algorithm, 3x3 and 5x5 masks, various metrics predefined



# Flood Filling

- Simple
- Gradient



Original image



Tolerance interval  $\pm 5$

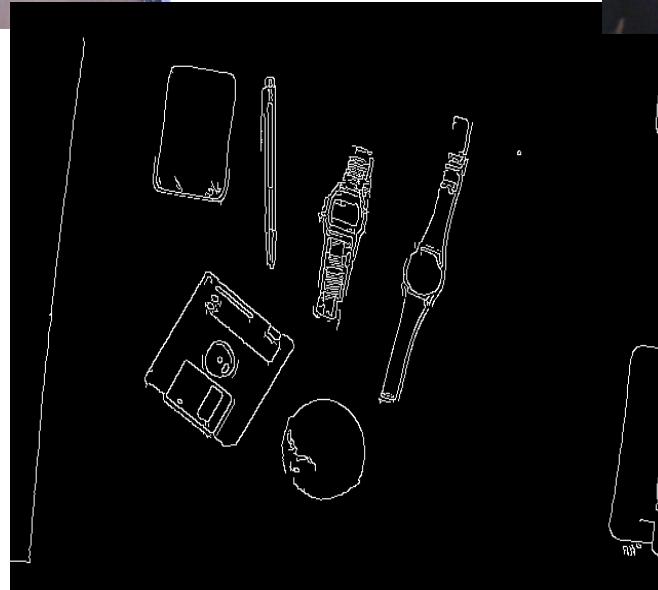


Tolerance interval  $\pm 6$

# Feature Detection

- Fixed filters (Sobel operator, Laplacian)
- Optimal filter kernels with floating point coefficients (first, second derivatives, Laplacian)
- Special feature detection (corners)
- Canny operator
- Hough transform (find lines and line segments)
- Gradient runs

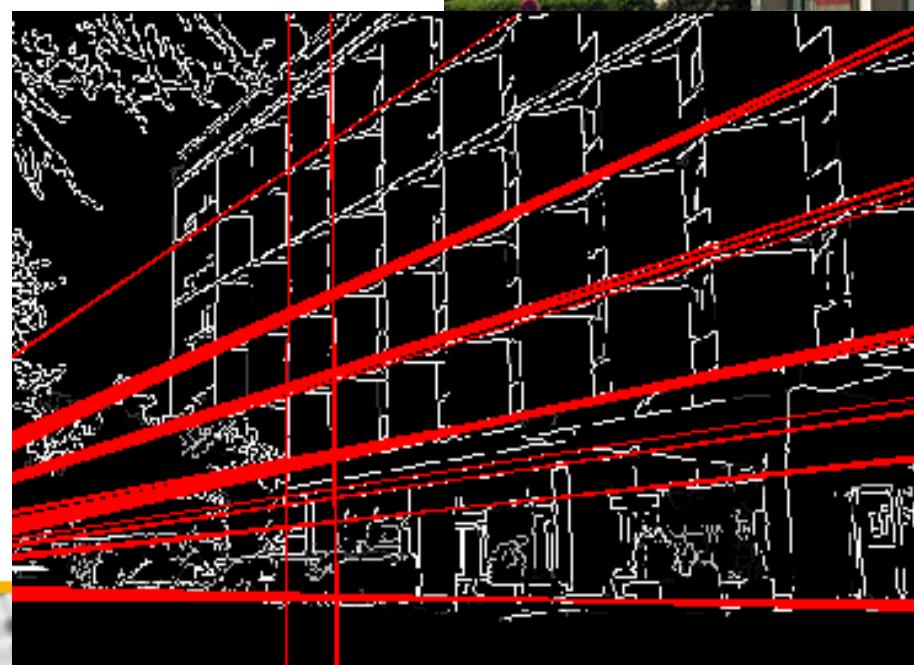
# Canny Edge Detector



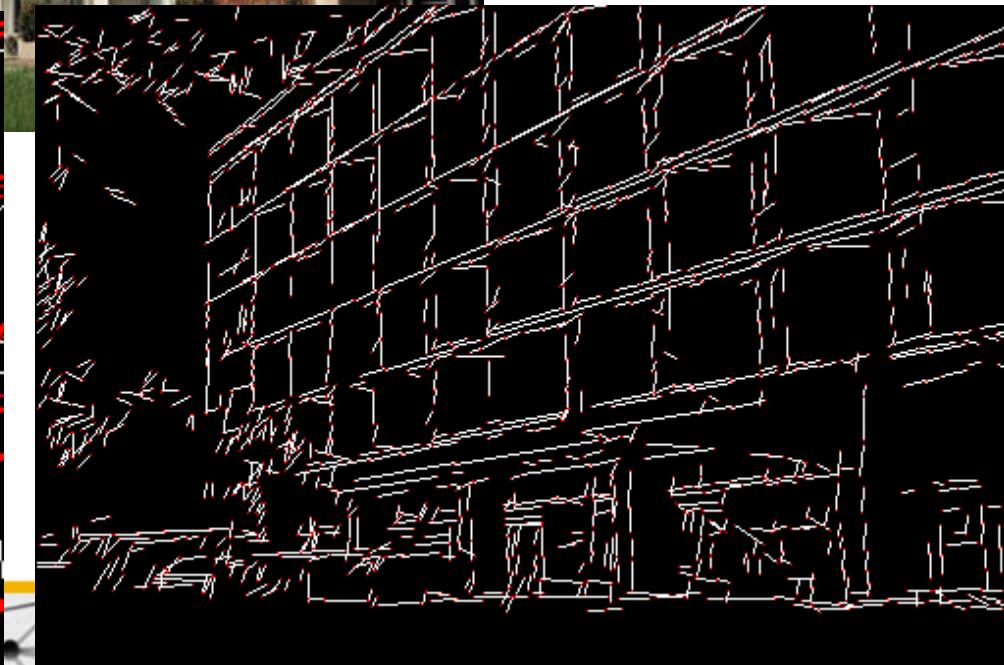
# Hough Transform

Detects lines in a binary image

- Standard Hough Transform

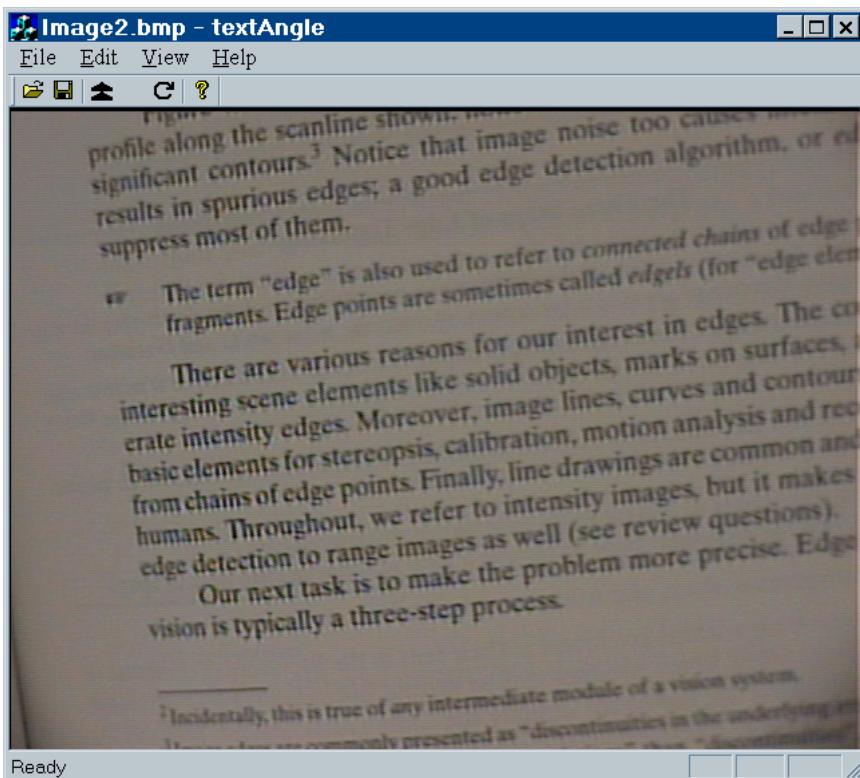


- Probabilistic Hough Transform

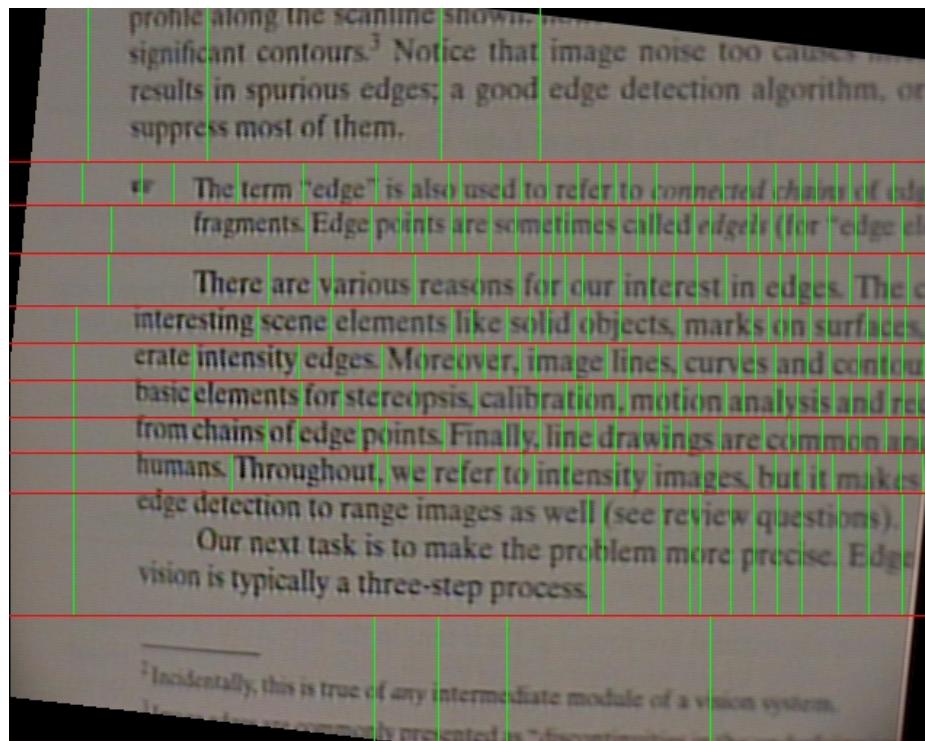


# Another Sample of the Hough Transform Using

## Source picture

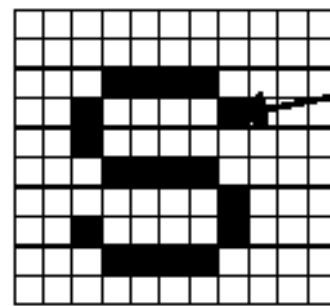


## Result



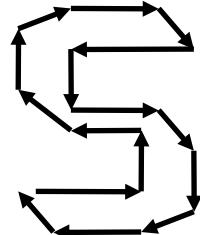
# Contour Retrieving

- The contour representation:
  - ✓ Chain code (Freeman code)
  - ✓ Polygonal representation



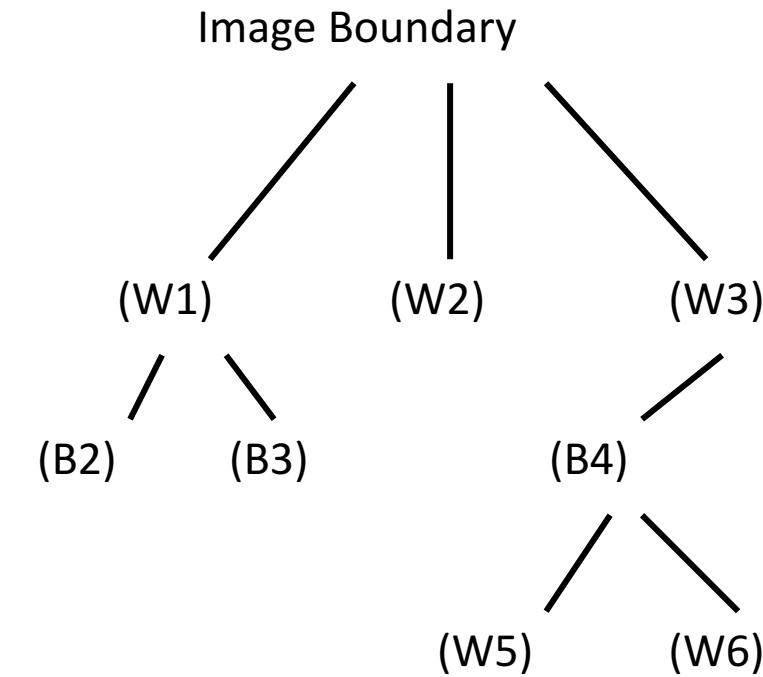
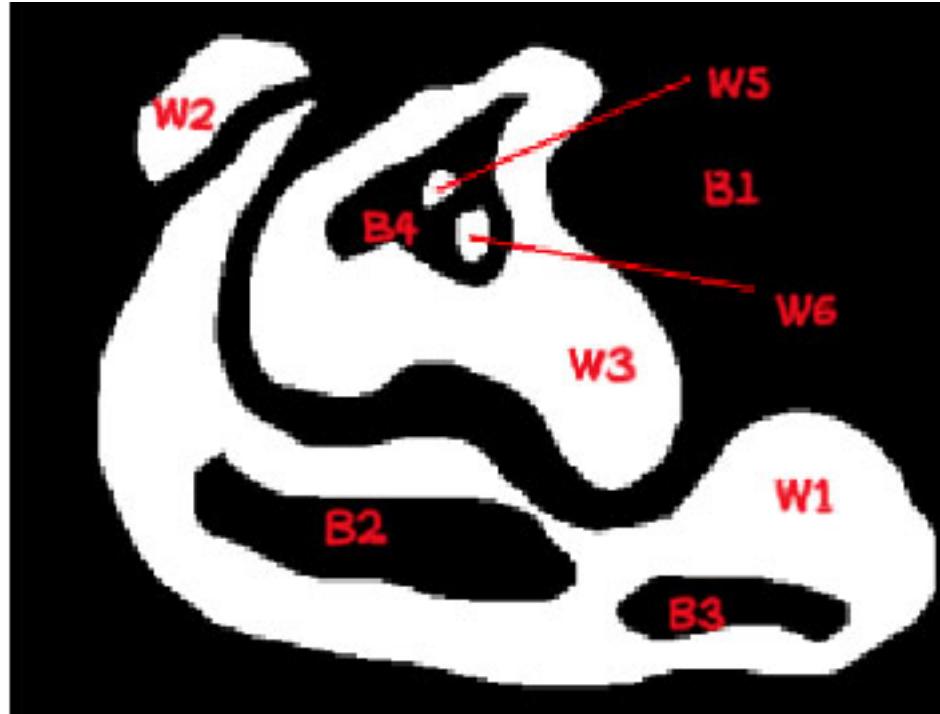
Initial Point

Chain code for the curve:  
34445670007654443



Contour representation

# Hierarchical representation of contours



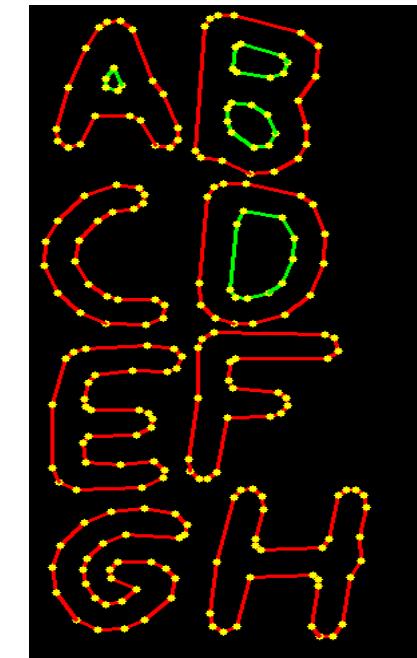
# Contours Examples



Source Picture  
( $300 \times 600 = 180000$  pts total)



Retrieved Contours  
(<1800 pts total)



After Approximation  
(<180 pts total)

And it is rather fast: ~70 FPS for 640x480 on complex scenes

# Structural Analysis

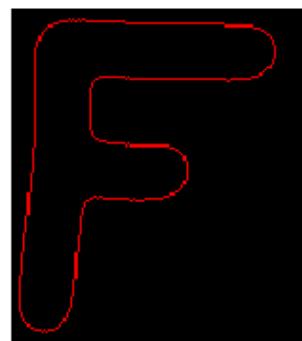


# Structural Analysis

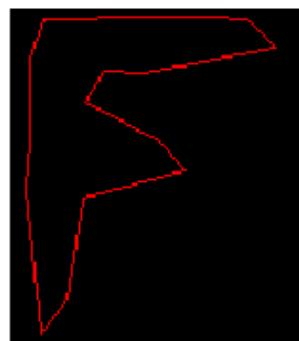
- Contours processing
  - Approximation
  - Hierarchical representation
  - Shape characteristics
  - Matching
- Geometry
  - Contour properties
  - Fitting with primitives
  - PGH: pair-wise geometrical histogram for the contour.

# Contour Processing

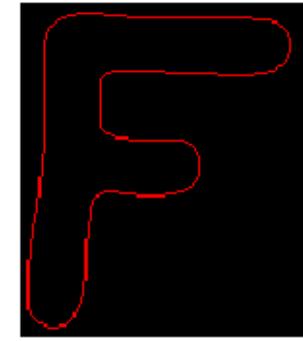
- Approximation:
  - ✓ RLE algorithm (chain code)
  - ✓ Teh-Chin approximation (polygonal)
  - ✓ Douglas-Peucker approximation (polygonal);
- Contour moments (central and normalized up to order 3)
- Hierarchical representation of contours
- Matching of contours



Source Image



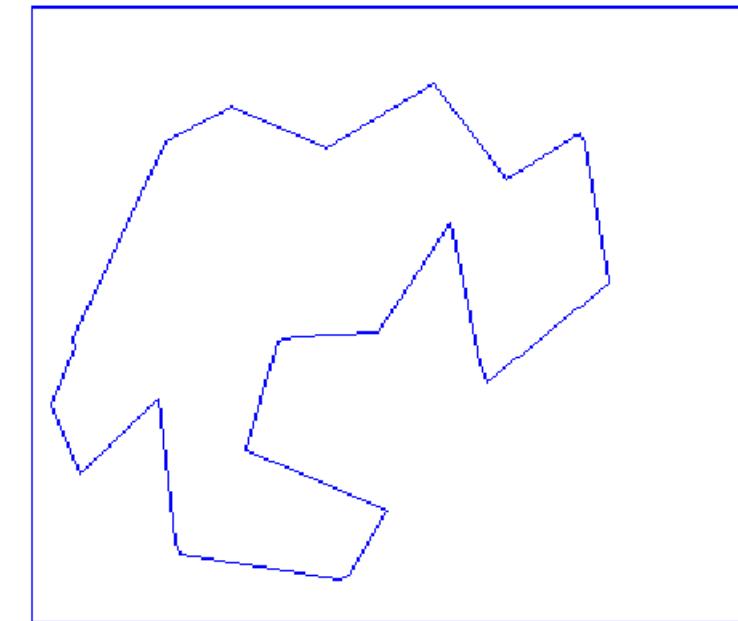
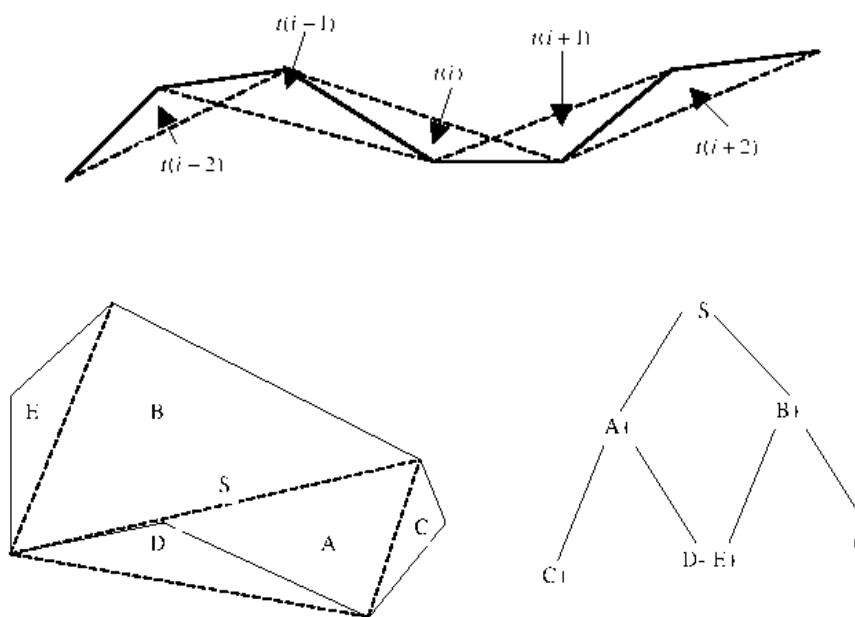
Rosenfeld-Johnston Algorithm Output



Teh-Chin Algorithm Output

# Hierarchical Representation of Contours

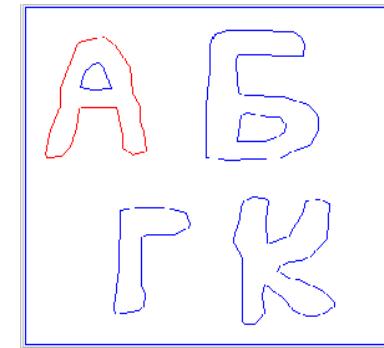
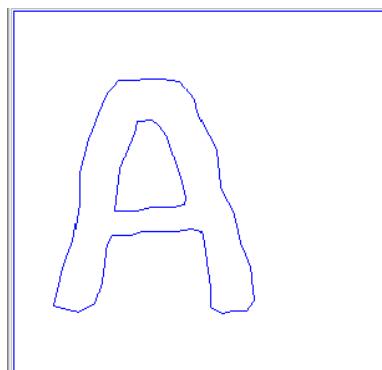
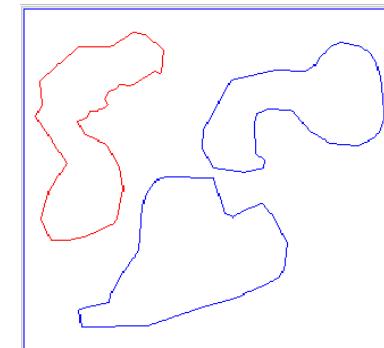
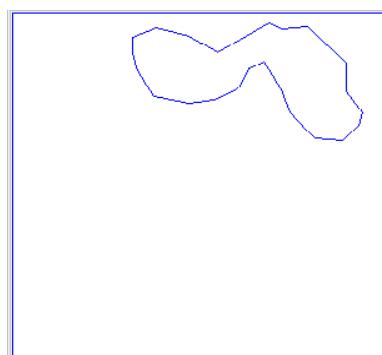
- A contour is represented with a binary tree
- Given the binary tree, the contour can be retrieved with arbitrary precision
- The binary tree is quasi invariant to translations, rotations and scaling



# Contours matching

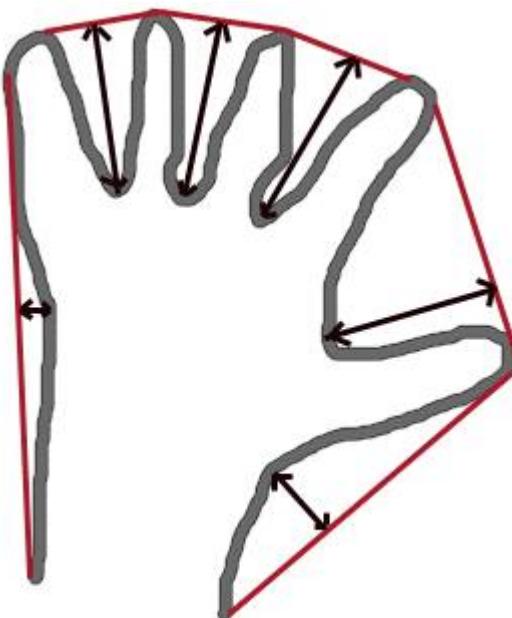
- Matching based on hierarchical representation of contours

Find all matching contours:



# Geometry

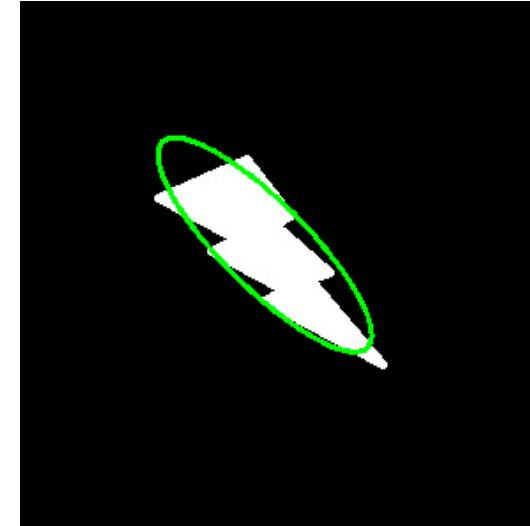
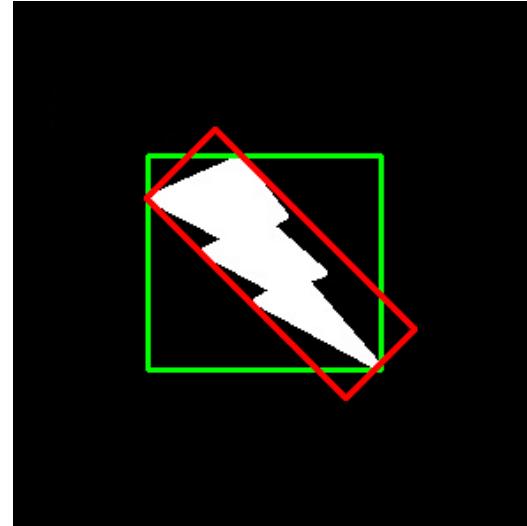
- Properties of contours: (perimeter, area, convex hull, convexity defects, rectangle of minimum area)
- Fitting: (2D line, 3D line, circle, ellipse)
- Pair-wise geometrical histogram



# Geometry

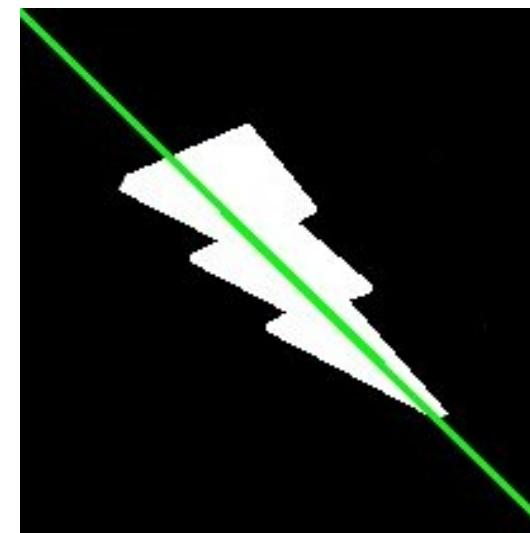
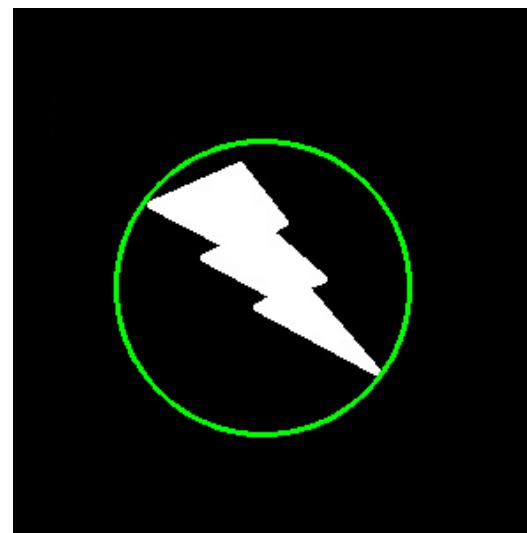
Bounding Rectangle:

- Straight Bounding Rectangle
- Rotated Rectangle



Fitting an Ellipse

Minimum Enclosing Circle



Fitting a Line

# Object Recognition



# Object Recognition

- Eigen objects
- Hidden Markov Models

# Eigen Objects

$u^i = \{u_1^i, u_2^i, \dots, u_n^i\} \in R^n, 1 \leq i \leq m, m \ll n,$

$C = \{C_{ij}\}$  – covariance matrix,

$$c_{ij} = \sum_l (u_l^i - \bar{u}_l) \cdot (u_l^j - \bar{u}_l), \quad \bar{u}_l = 1/m \sum_{k=1}^m u_l^k,$$

$$e_l^i = 1/\sqrt{\lambda_i} \sum_k v_k^i \cdot (u_l^i - \bar{u}_l),$$

$e^i = \{e_1^i, e_2^i, \dots, e_n^i\}, i = 1, \dots, m_1 \leq m$  – eigen basis,

$\lambda_i$  and  $v^i = \{v_1^i, v_2^i, \dots, v_m^i\}$  – eigen values and eigen vectors.

# Eigen Objects: result



# Hidden Markov Model Definitions

$S = \{s_1, s_2, \dots, s_N\}$  - The set of states

$O = \{o_1, o_2, \dots, o_M\}$  - The set of measurements

$q_t \in O$  - The state at time  $t$

$A = \{a_{ij} \setminus a_{ij} = P(q_t = s_j \mid q_{t-1} = s_i)\}$  - The transition probability matrix

$B = \{b_{ij} \setminus b_{ij} = P(o_i \mid s_j)\}$  - The conditional probability matrix

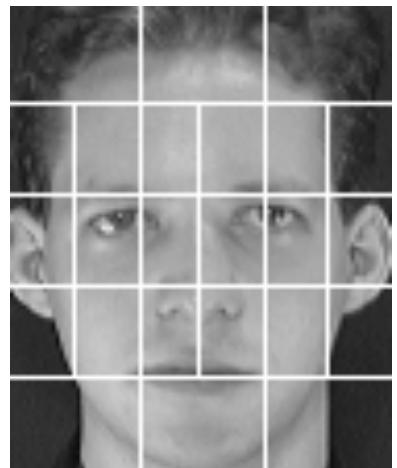
$\Pi = \{\pi_i \setminus \pi_i = P(q_0 = s_i)\}$  - The starting states distribution

# Hidden Markov Model Algorithms

- Model parameters estimation
- Recognition
- Viterbi algorithm

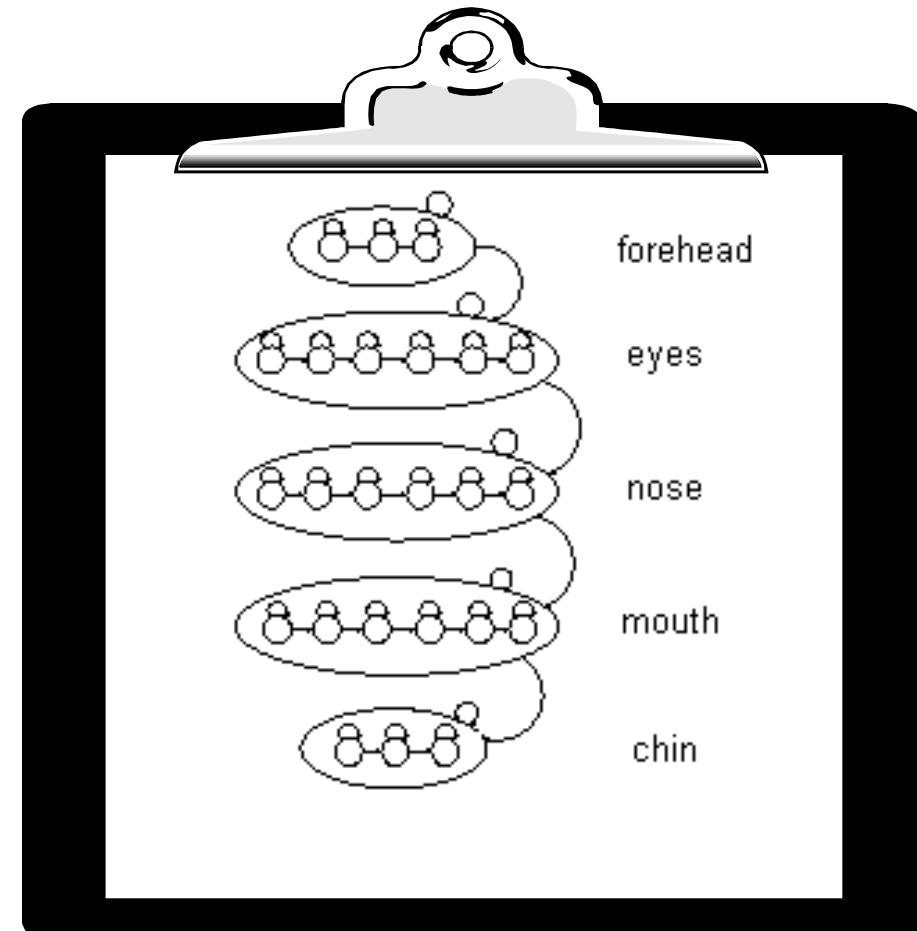


# Embedded HMM for Face Recognition



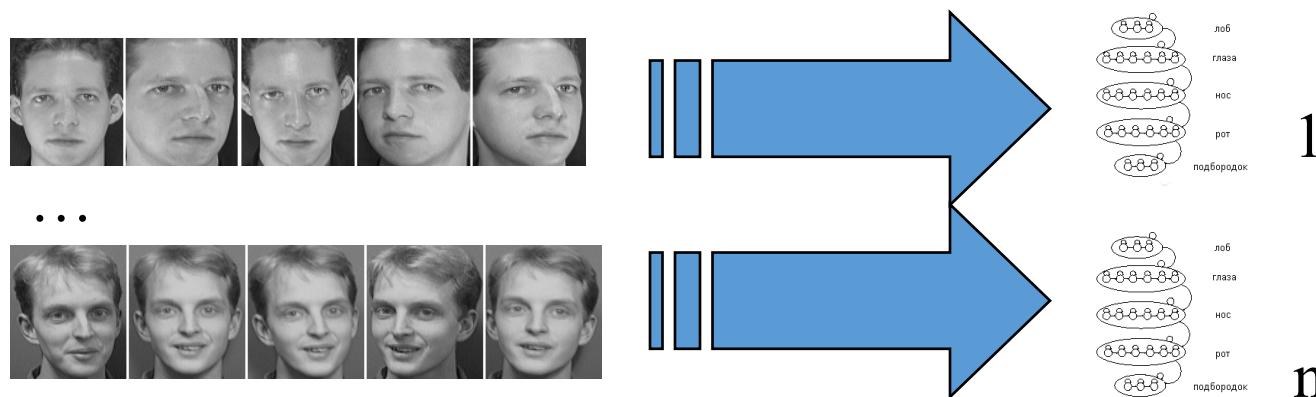
- Face ROI partition

Model-

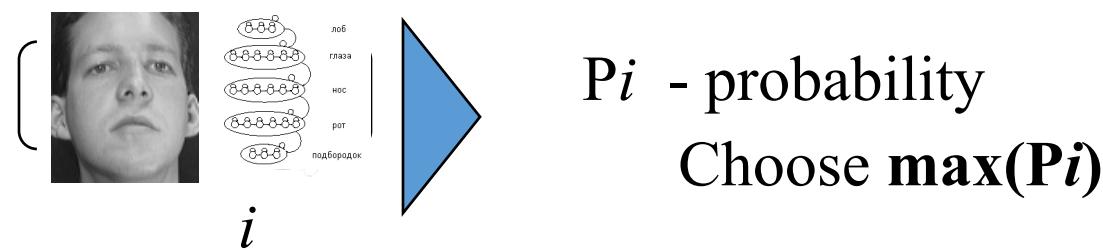


# Face recognition using Hidden Markov Models

- One person – one HMM
- Stage 1 – Train every HMM



- Stage 2 – Recognition



# Motion Analysis and Object Tracking



# Motion Analysis and Object Tracking

- Background subtraction
- Motion templates
- Optical flow
- Active contours
- Estimators



# Background Subtraction

- Background model (normal distribution)
- Background statistics functions:
  - ✓ Average
  - ✓ Standard deviation
  - ✓ Running average



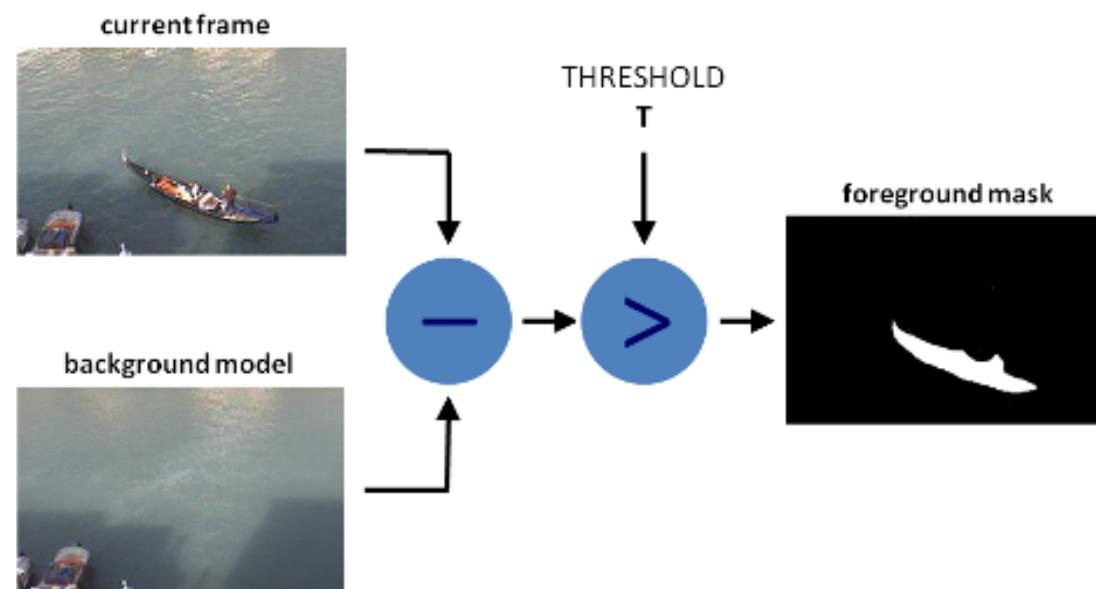
# Running average

- Computes the sum of two images:

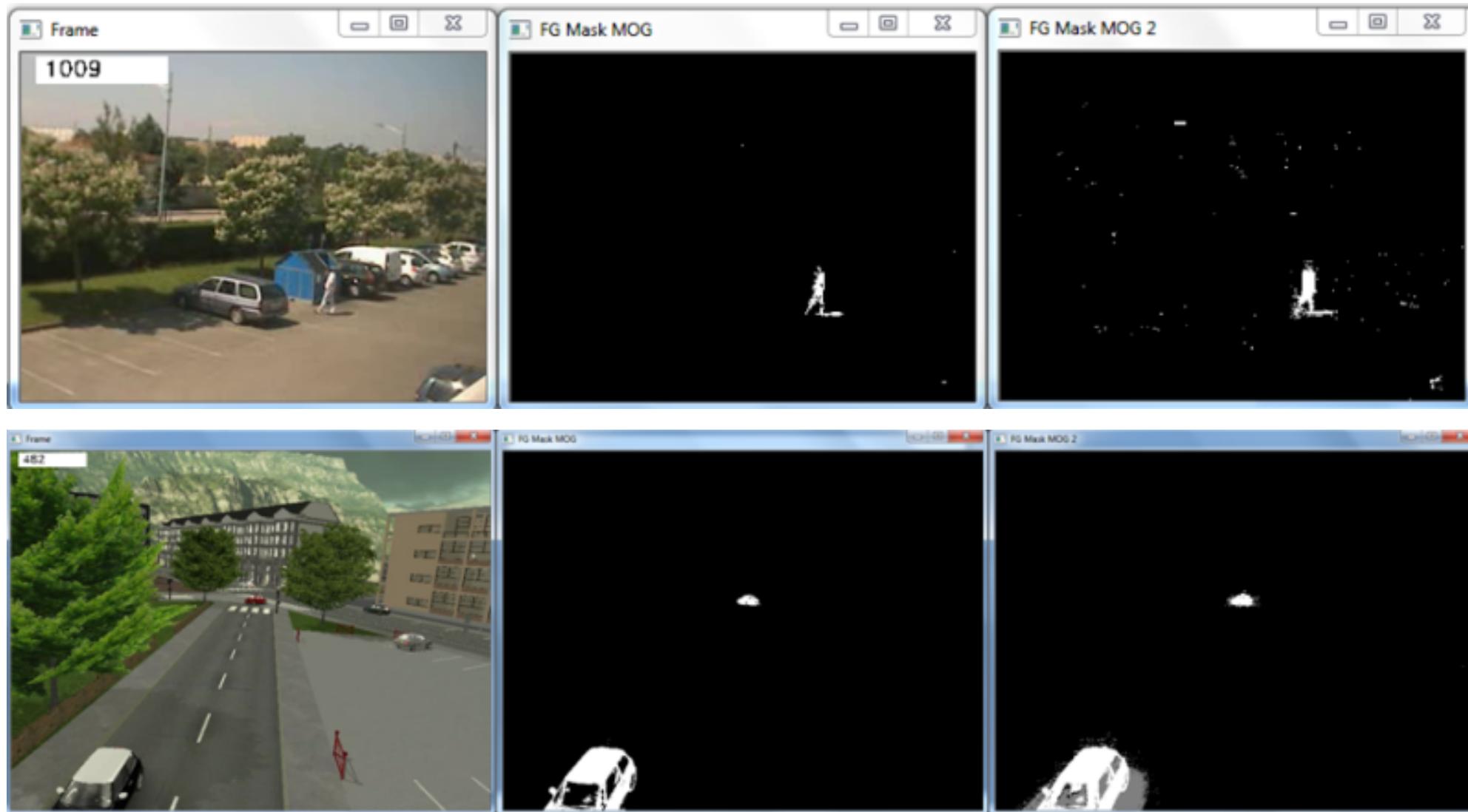
$$\mu_{ij}^t = \alpha \cdot I_{ij}^t + (1 - \alpha) \cdot \mu_{ij}^{t-1}, \quad 0 \leq \alpha \leq 1$$

# Background Subtraction Example

- Background subtraction (BS) is a common and widely used technique for generating a foreground mask (namely, a binary image containing the pixels belonging to moving objects in the scene) by using static cameras.
- As the name suggests, BS calculates the foreground mask performing a subtraction between the current frame and a background model, containing the static part of the scene or, more in general, everything that can be considered as background given the characteristics of the observed scene.



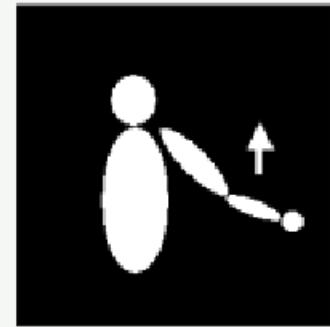
# Background Subtraction Example



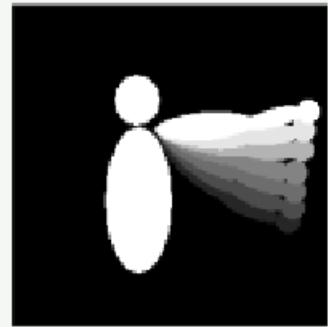
# Motion Templates

- Object silhouette
- Motion history images
- Motion history gradients
- Motion segmentation algorithm

silhouette



MHI

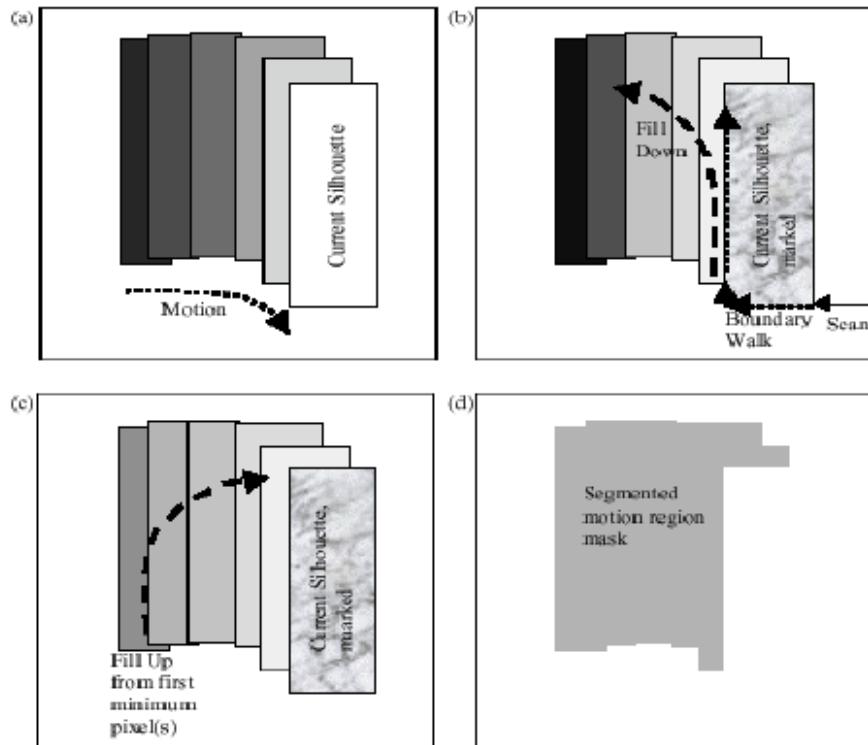


MHG

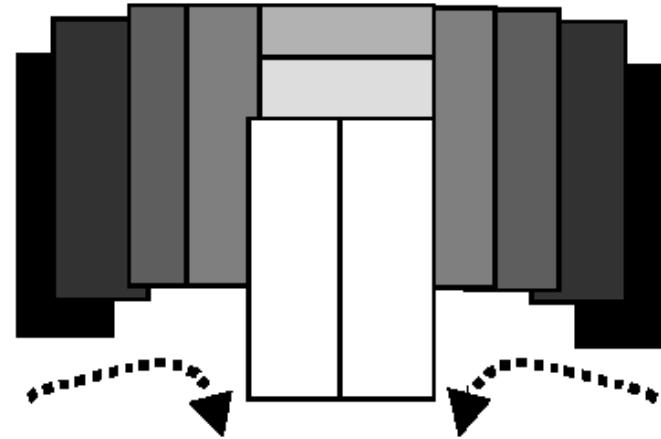


# Motion Segmentation Algorithm

- Two-pass algorithm labeling all motion segments

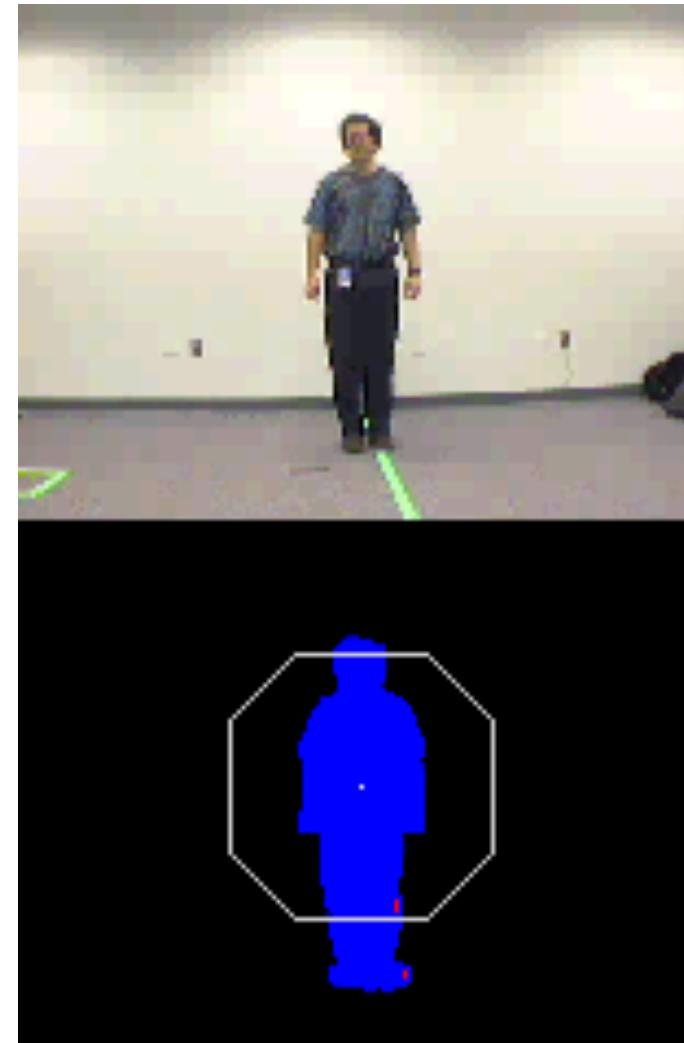


Clapping boxes together and down



# Motion Templates Example

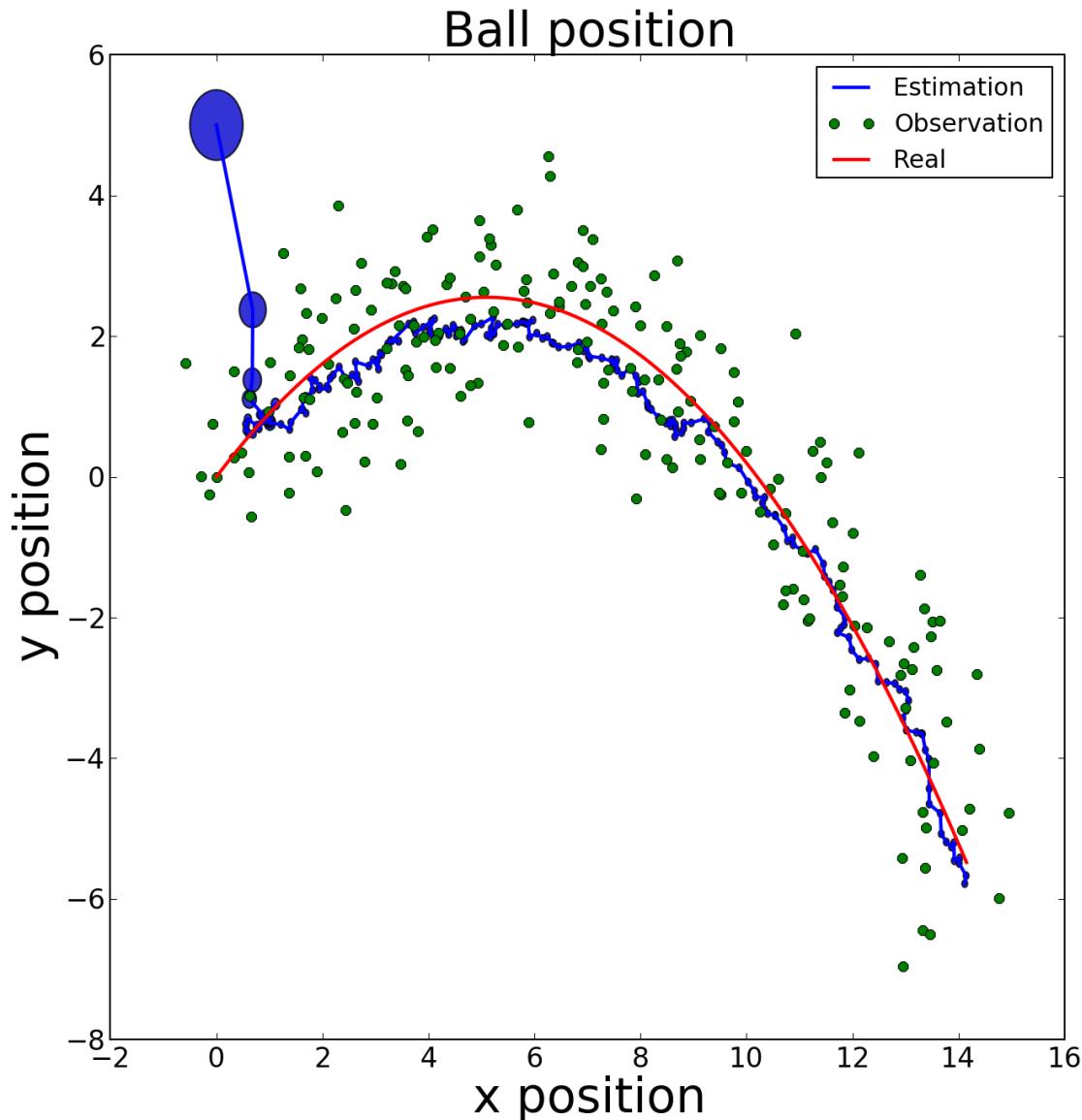
- Motion templates allow to retrieve the dynamic characteristics of the moving object



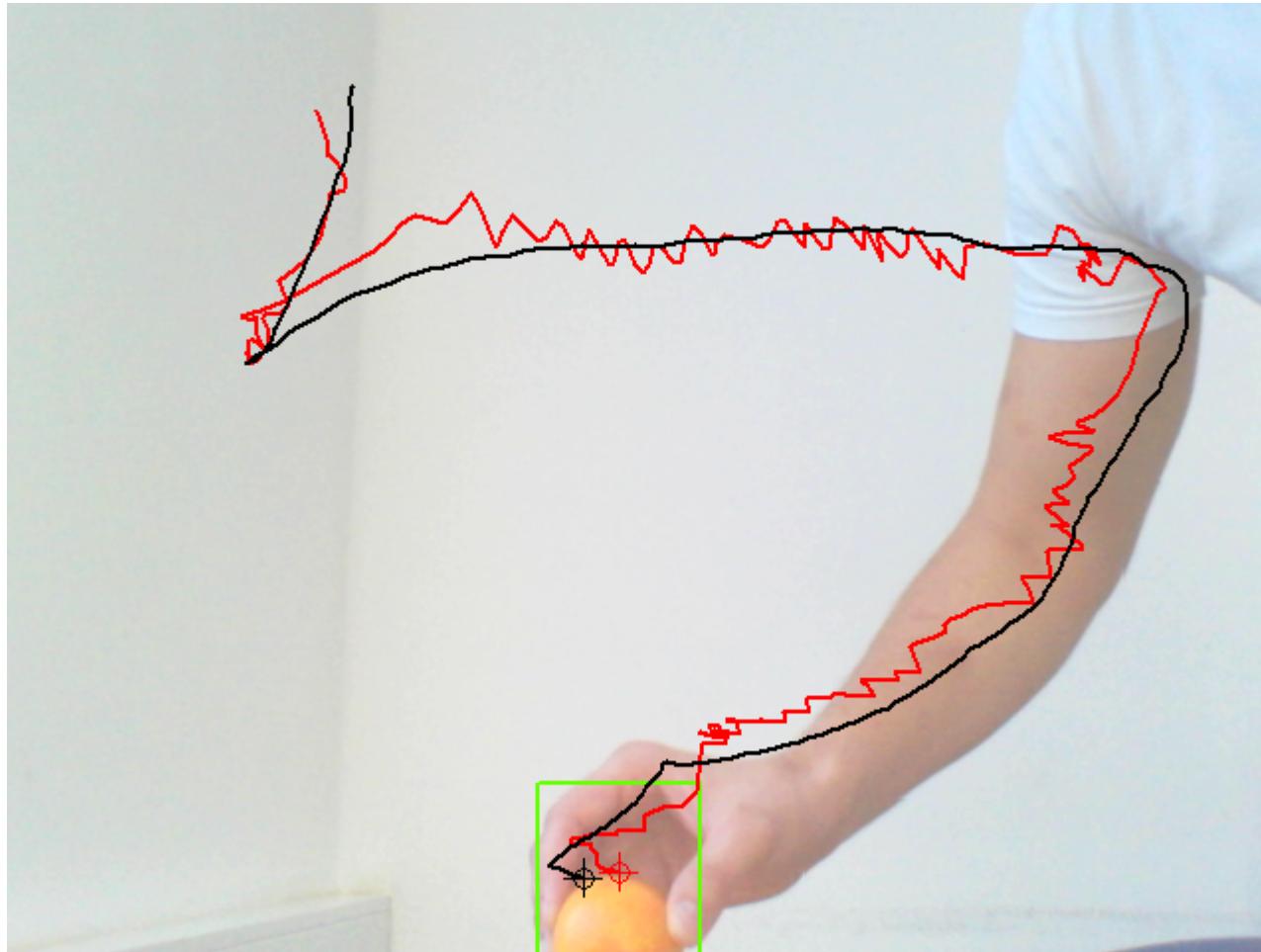
# Kalman filter object tracker

- Smooth track line by set of noisy estimations
- Prediction the next points of track

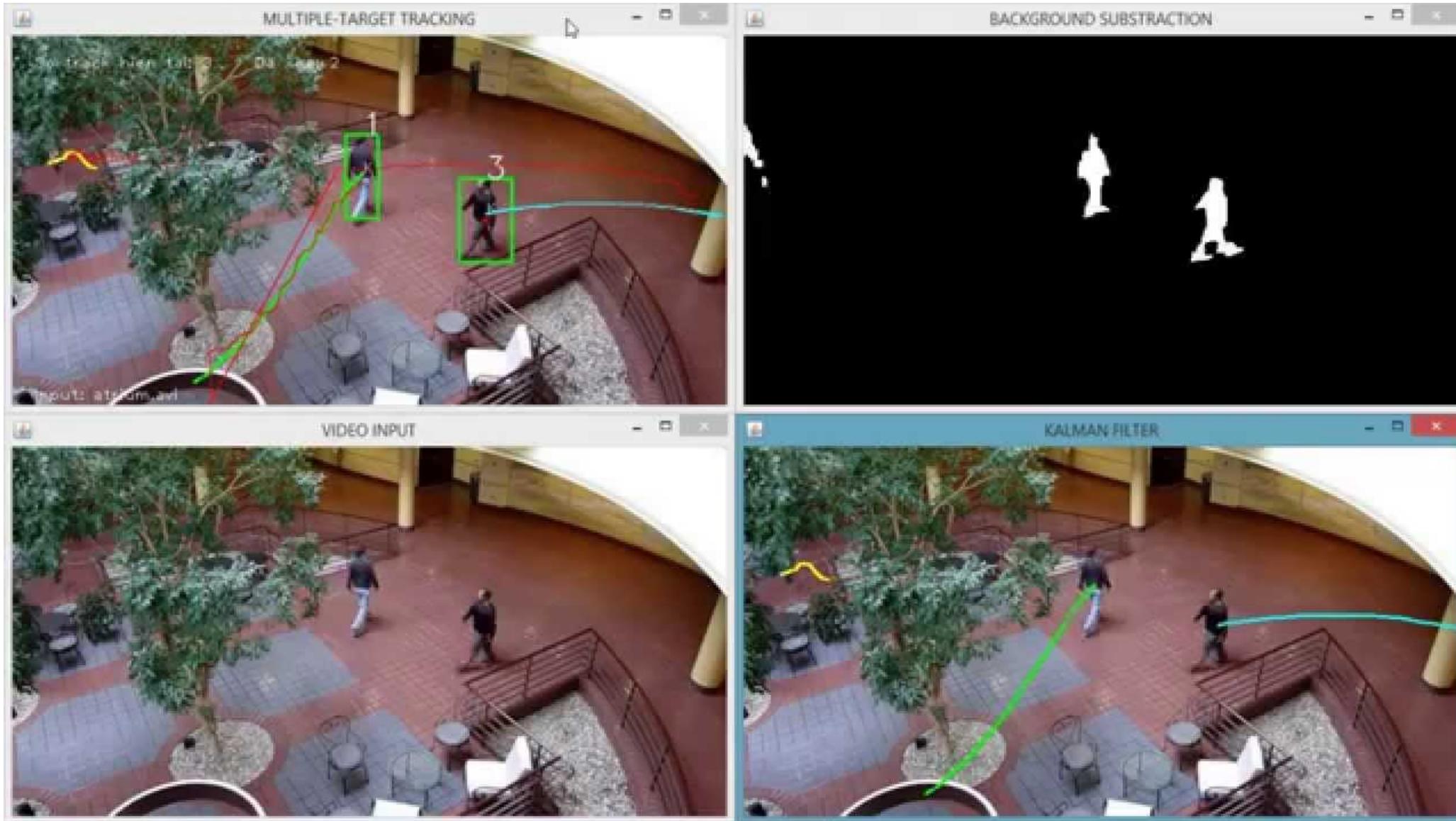
# Kalman filter object tracker: smooth



# Kalman filter object tracker: single object



# Kalman filter object tracker: multi object



# 3D reconstruction



# 3D reconstruction

- Camera Calibration
- View Morphing
- POSIT



# Camera Calibration

- Define intrinsic and extrinsic camera parameters.
- Define Distortion parameters

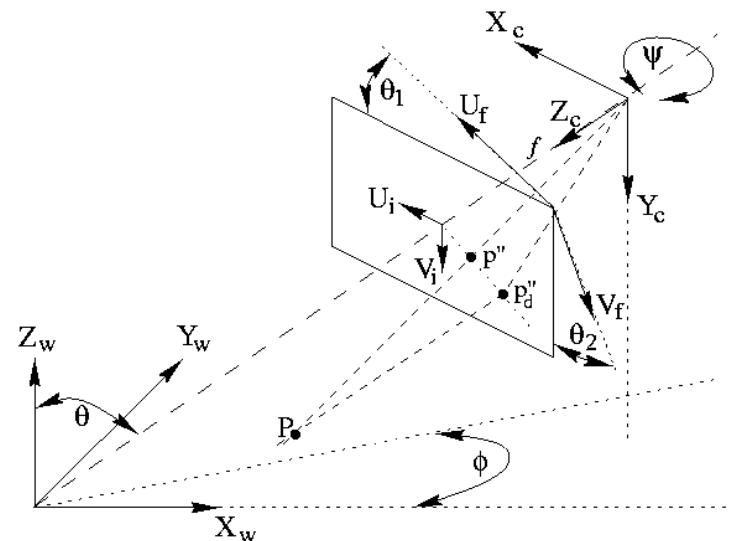
$$p = A[RT]P,$$

$$A = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}, \quad R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}, \quad T = \begin{bmatrix} t_1 \\ t_2 \\ t_3 \end{bmatrix}, \quad P = [X, Y, Z], \quad p = [u, v]$$

$$\tilde{u} = u + (u - c_x) \cdot [k_1 \cdot r^2 + k_2 \cdot r^4 + 2p_1y + p_2(r^2/x + 2x)],$$

$$\tilde{v} = v + (v - c_y) \cdot [k_1 \cdot r^2 + k_2 \cdot r^4 + 2p_2x + p_1(r^2/y + 2y)],$$

$$r^2 = x^2 + y^2.$$

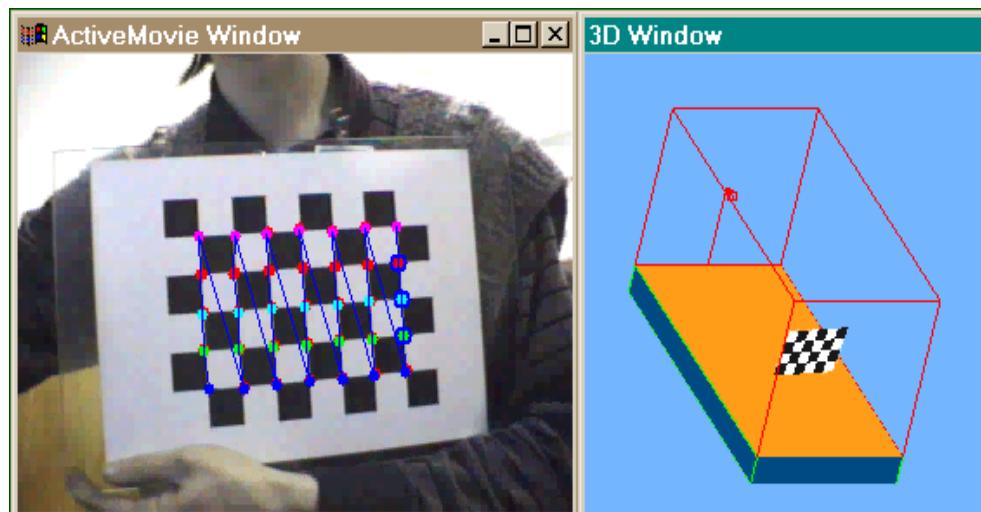


# Camera Calibration

Now, camera calibration can be done by holding checkerboard in front of the camera for a few seconds.

And after that you'll get:

***3D view of etalon***



***Un-distorted image***



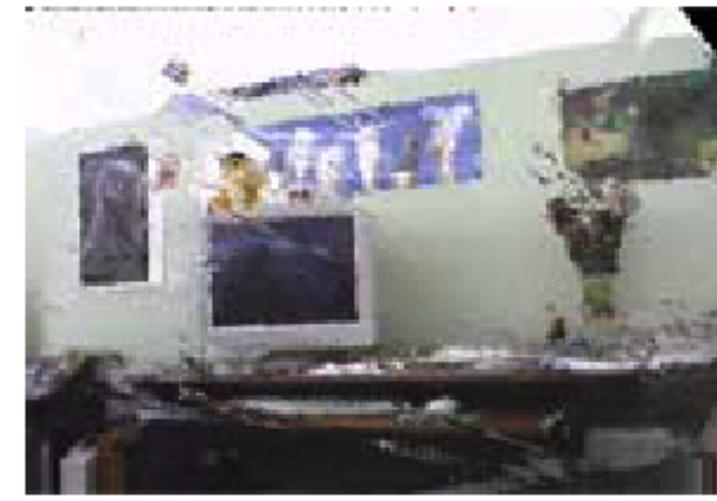
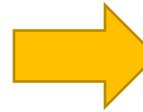
# View Morphing



Original Image From Left Camera



Original Image From Right Camera

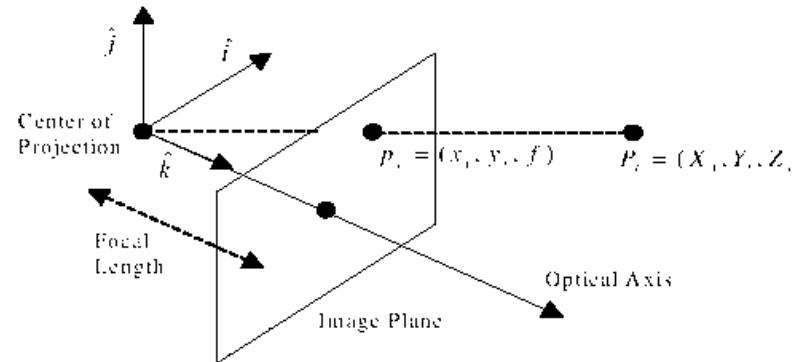


***Result***

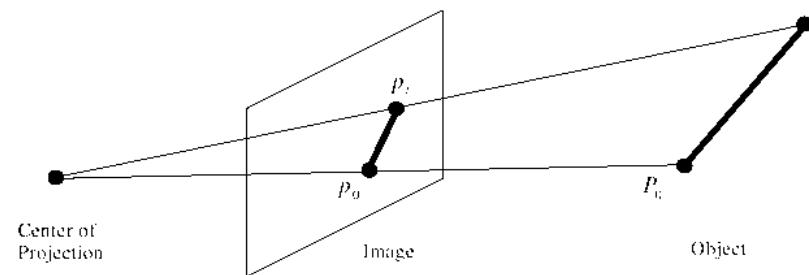
# POSIT Algorithm

- Perspective projection:

$$x_i = (f/Z_i) \cdot X_i, y_i = (f/Z_i) \cdot Y_i$$



- Weak-perspective projection:  $x_i = s \cdot X_i, y_i = s \cdot Y_i, s = f/Z$ .



# References

- Gunilla Borgefors. *Distance Transformations in Digital Images*. Computer Vision, Graphics and Image Processing 34, 344-371,(1986).
- G. Bradski and J. Davis. *Motion Segmentation and Pose Recognition with Motion History Gradients*. IEEE WACV'00, 2000.
- P. J. Burt, T. H. Hong, A. Rosenfeld. *Segmentation and Estimation of Image Region Properties Through Cooperative Hierarchical Computation*. IEEE Tran. On SMC, Vol. 11, N.12, 1981, pp.802-809.
- J.Canny. *A Computational Approach to Edge Detection*, IEEE Trans. on Pattern Analysis and Machine Intelligence, 8(6), pp.679-698 (1986).
- J. Davis and Bobick. *The Representation and Recognition of Action Using Temporal Templates*. MIT Media Lab Technical Report 402,1997.
- Daniel F. DeMenthon and Larry S. Davis. *Model-Based Object Pose in 25 Lines of Code*. In Proceedings of ECCV '92, pp. 335-343, 1992.
- Andrew W. Fitzgibbon, R.B.Fisher. *A Buyer's Guide to Conic Fitting*. Proc. 5 th British Machine Vision Conference, Birmingham, pp. 513-522, 1995.
- Berthold K.P. Horn and Brian G. Schunck. *Determining Optical Flow*. Artificial Intelligence, 17, pp. 185-203, 1981.

# References

- M.Hu.*Visual Pattern Recognition by Moment Invariants*, IRE Transactions on Information Theory, 8:2, pp. 179-187, 1962.
- B. Jahne. *Digital Image Processing*. Springer, New York, 1997.
- M. Kass, A. Witkin, and D. Terzopoulos. *Snakes: Active Contour Models*, International Journal of Computer Vision, pp. 321-331, 1988.
- J.Matas, C.Galambos, J.Kittler. *Progressive Probabilistic Hough Transform*. British Machine Vision Conference, 1998.
- A. Rosenfeld and E. Johnston. *Angle Detection on Digital Curves*. IEEE Trans. Computers, 22:875-878, 1973.
- Y.Rubner.C.Tomasi,L.J.Guibas.*Metrics for Distributions with Applications to Image Databases*. Proceedings of the 1998 IEEE International Conference on Computer Vision, Bombay, India, January 1998, pp. 59-66.
- Y. Rubner. C. Tomasi, L.J. Guibas. *The Earth Mover's Distance as a Metric for Image Retrieval*. Technical Report STAN-CS-TN-98-86, Department of Computer Science, Stanford University, September, 1998.
- Y.Rubner.C.Tomasi.*Texture Metrics*. Proceeding of the IEEE International Conference on Systems, Man, and Cybernetics, San-Diego, CA, October 1998, pp. 4601- 4607. <http://robotics.stanford.edu/~rubner/publications.html>

# References

- J. Serra. *Image Analysis and Mathematical Morphology*. Academic Press, 1982.
- Bernt Schiele and James L. Crowley. *Recognition without Correspondence Using Multidimensional Receptive Field Histograms*. In International Journal of Computer Vision 36 (1), pp. 31-50, January 2000.
- S. Suzuki, K. Abe. *Topological Structural Analysis of Digital Binary Images by Border Following*. CVGIP, v.30, n.1. 1985, pp. 32-46.
- C.H.Teh, R.T.Chin. *On the Detection of Dominant Points on Digital Curves*. - IEEE Tr. PAMI, 1989, v.11, No.8, p. 859-872.
- Emanuele Trucco, Alessandro Verri. *Introductory Techniques for 3-D Computer Vision*. Prentice Hall, Inc., 1998.
- D. J. Williams and M. Shah. *A Fast Algorithm for Active Contours and Curvature Estimation*. CVGIP: Image Understanding, Vol. 55, No. 1, pp. 14-26, Jan., 1992. <http://www.cs.ucf.edu/~vision/papers/shah/92/WIS92A.pdf>.
- A.Y.Yuille, D.S.Cohen, and P.W.Hallinan. *Feature Extraction from Faces Using Deformable Templates* in CVPR, pp. 104-109, 1989.
- Zhengyou Zhang. *Parameter Estimation Techniques: A Tutorial with Application to Conic Fitting*, Image and Vision Computing Journal, 1996.