Tracking

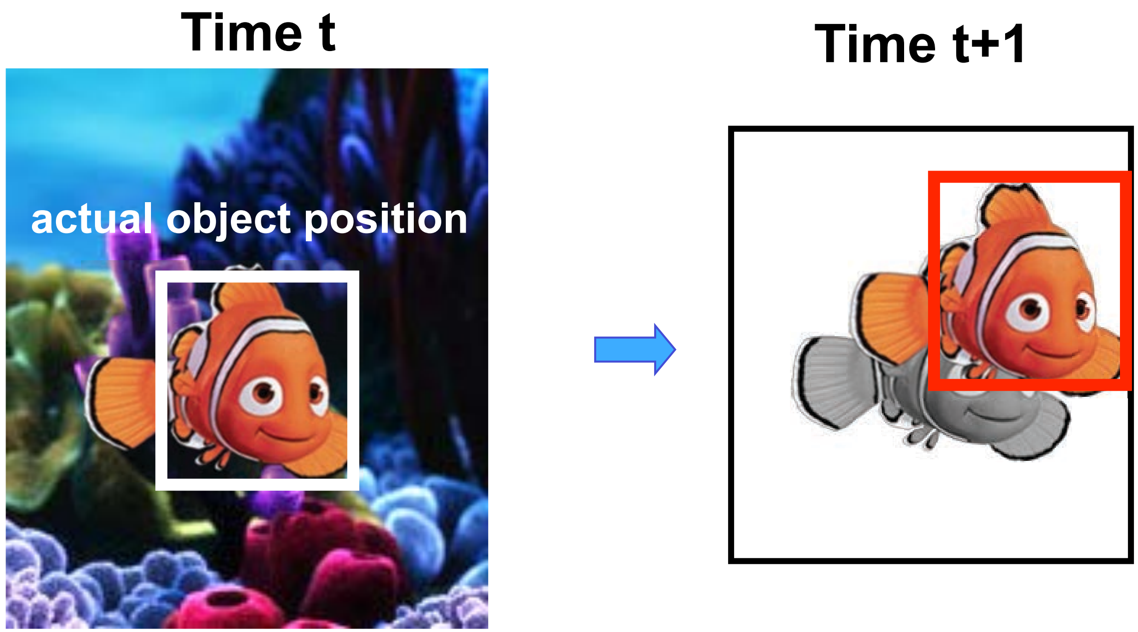
Dictionary:

- [noun] "The pursuit (of a person or animal) by following tracks or marks they left behind"
- [verb] "Observe or plot the moving path of something (e.g., to track a missile)"

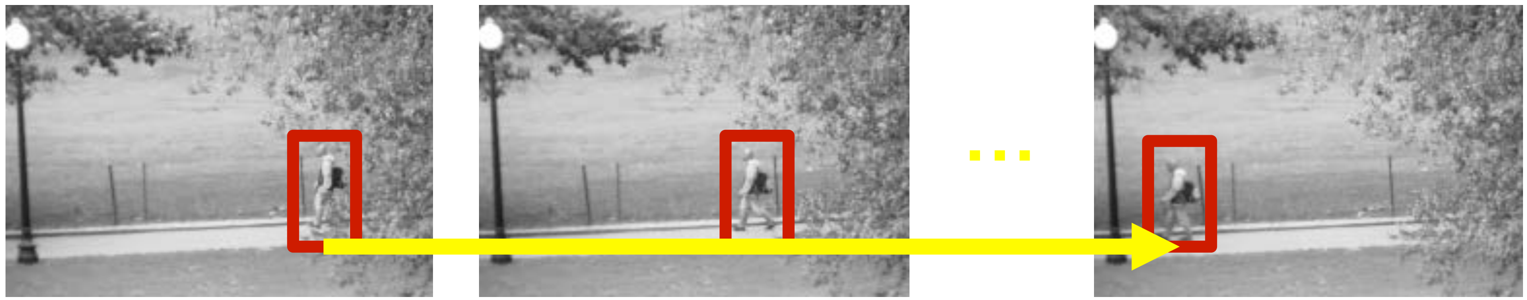
What does it mean in Computer Vision?

Many thanks to: H. Grabner, L. van Gool, and V. Ferrari for some of the slides & videos.

What is Tracking



LOCALIZE "*IT*" IN THE NEXT FRAMES



Computer Vision

Why do we need it

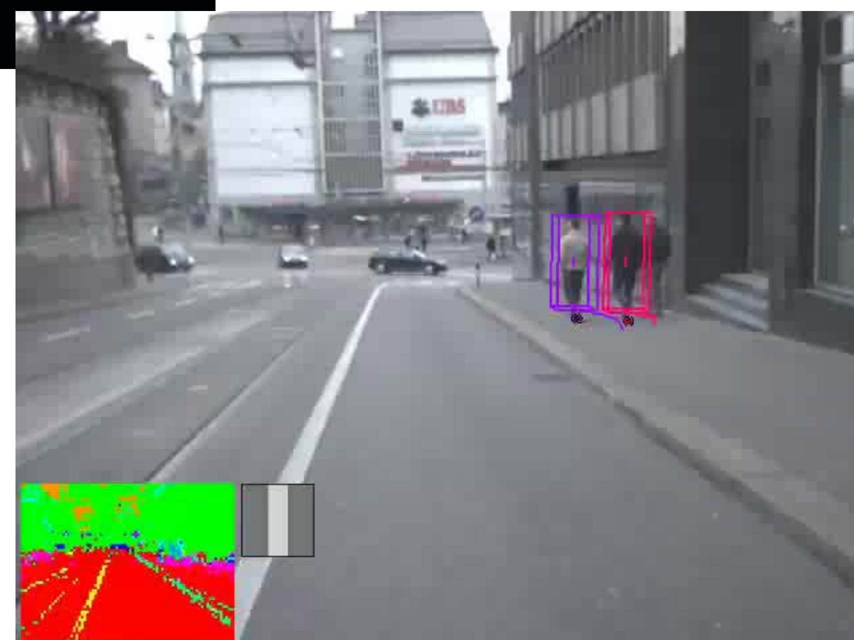
What is tracking for you? Why do you think it is relevant and may be important?

Where could it be useful, in real-life applications and engineering scenarios?

Task: "List <u>applications</u> you can think of on a piece of paper"

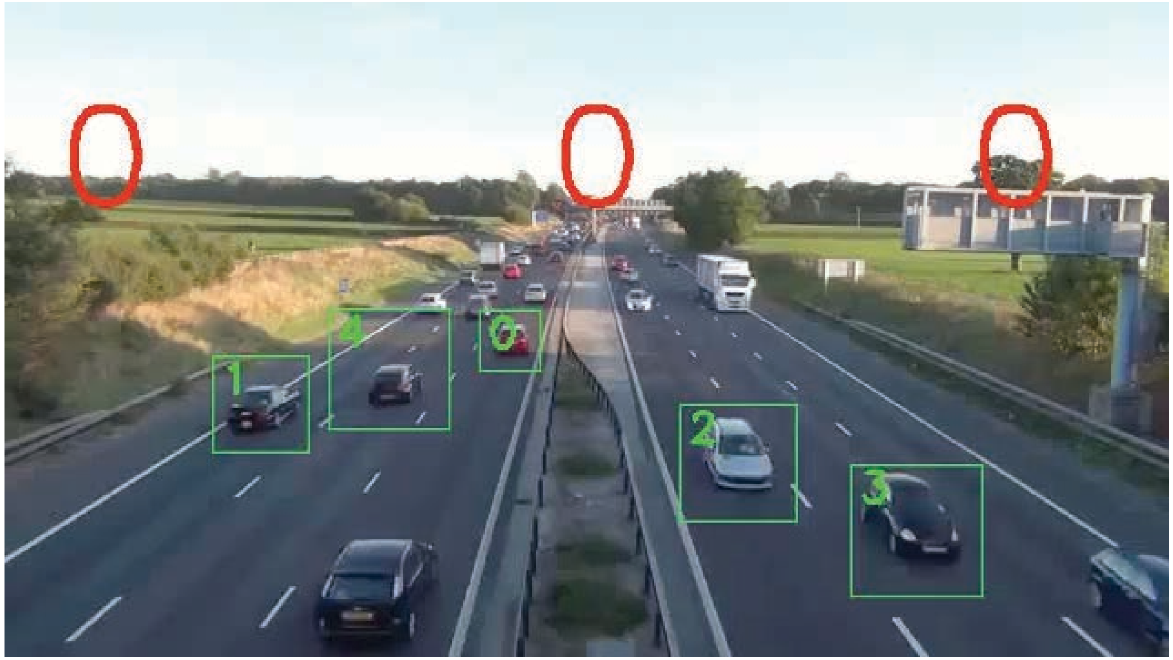
Discuss in groups of 3-4

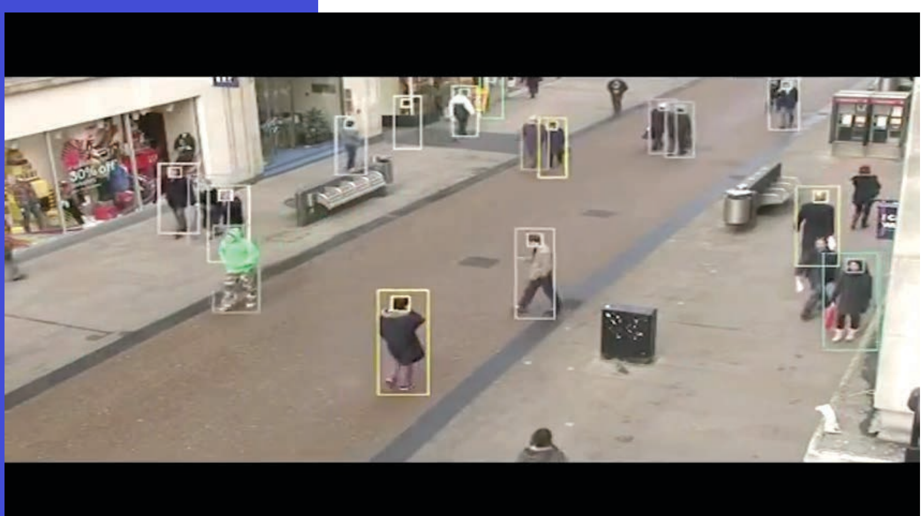
Autonomous Driving

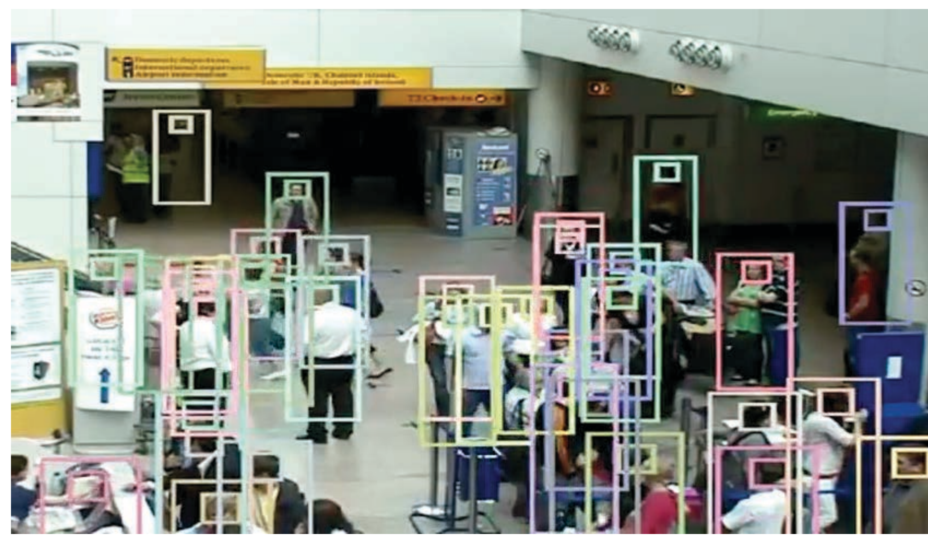


Computer Vision

Surveillance, Safety, Security

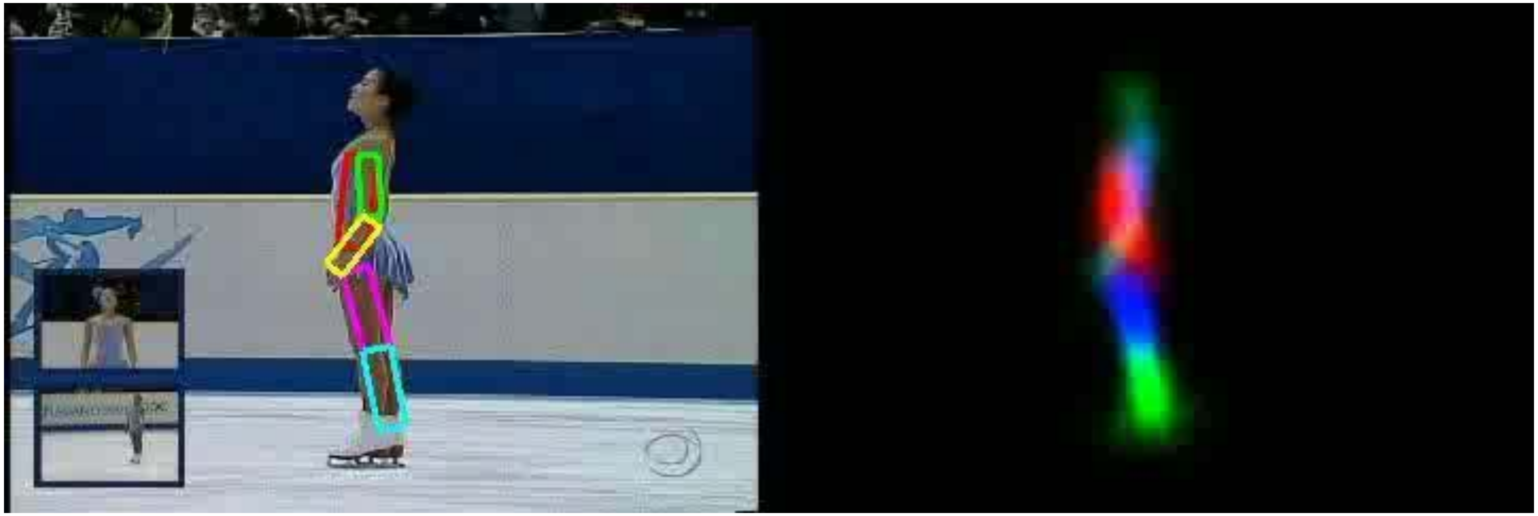






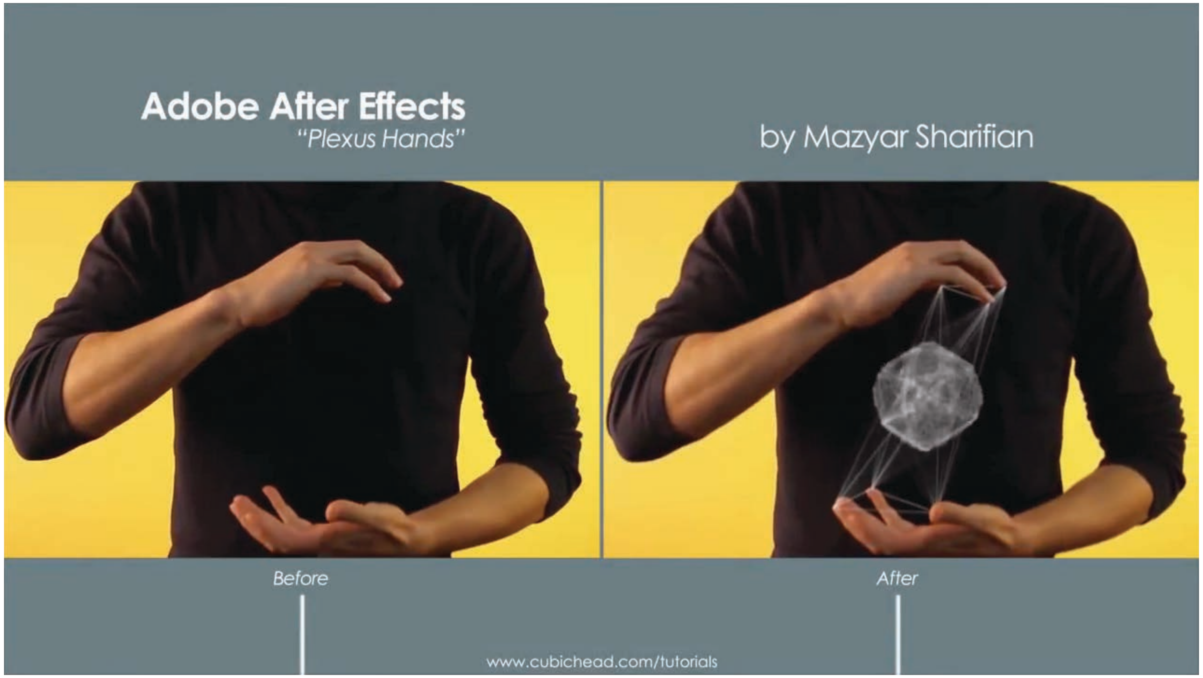
Computer Vision

Sports



Computer Vision

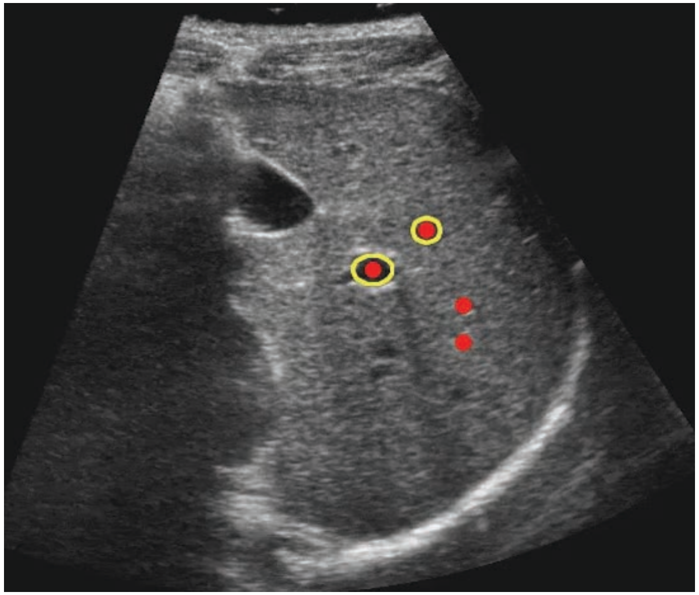
Video Editing

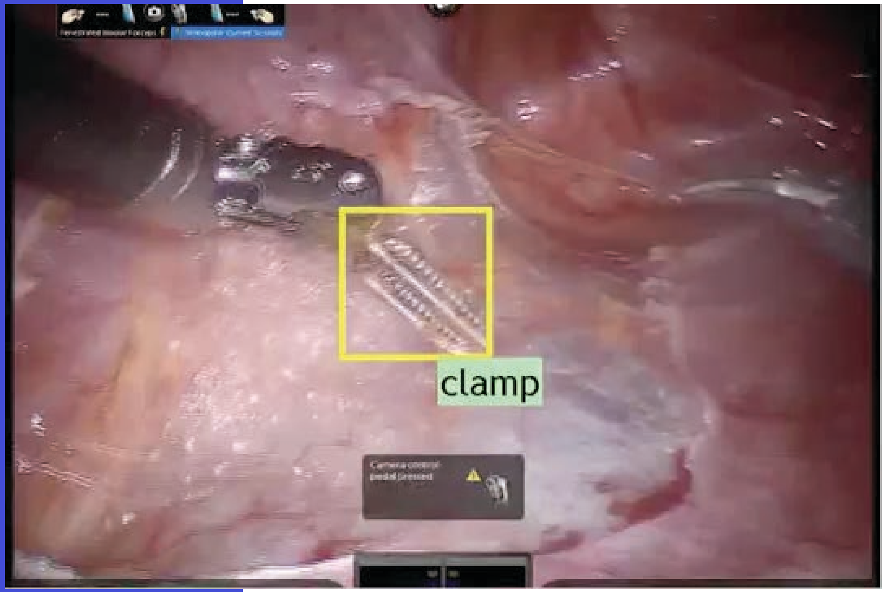


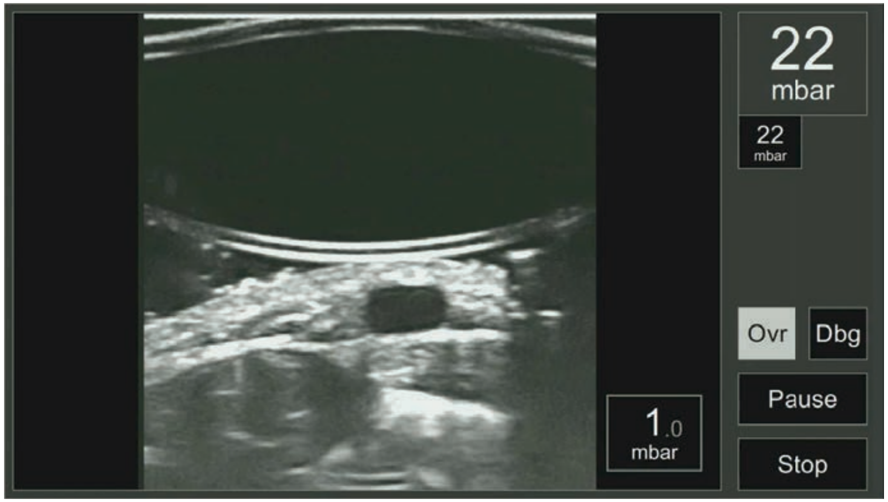
Applications: VR/AR glasses

Microsoft HoloLens

Medical Guidance

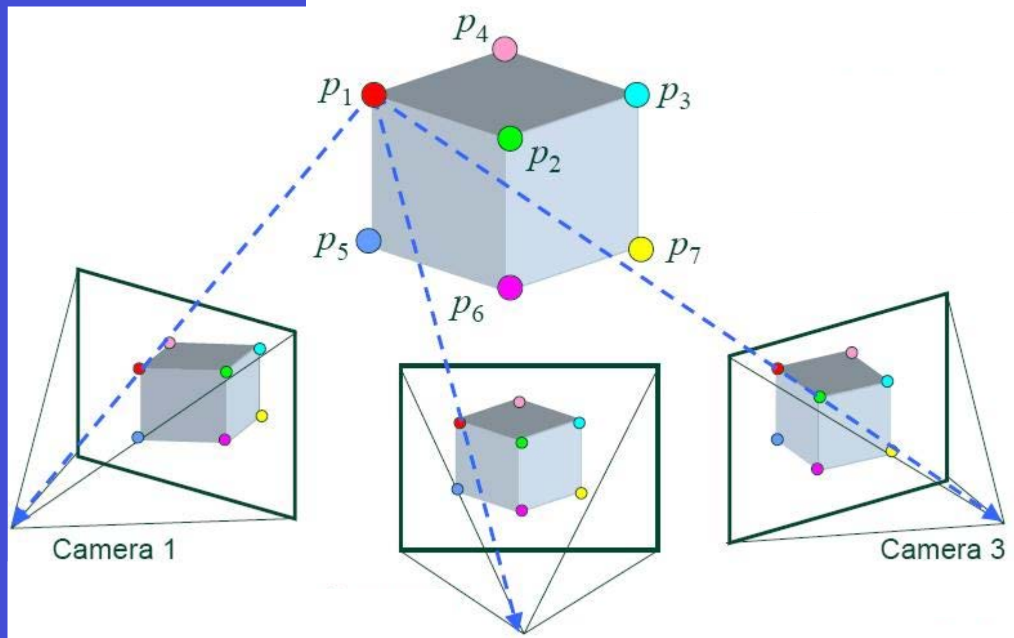


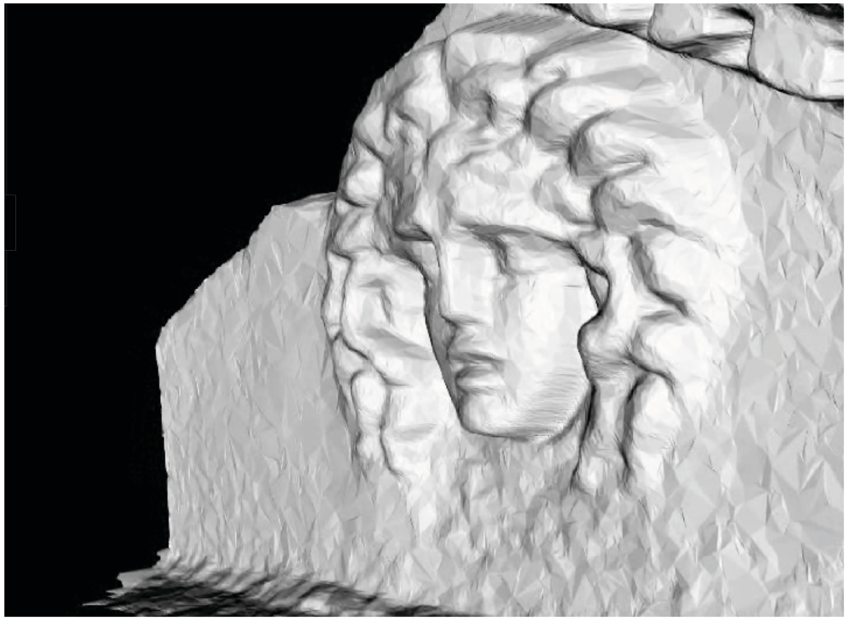




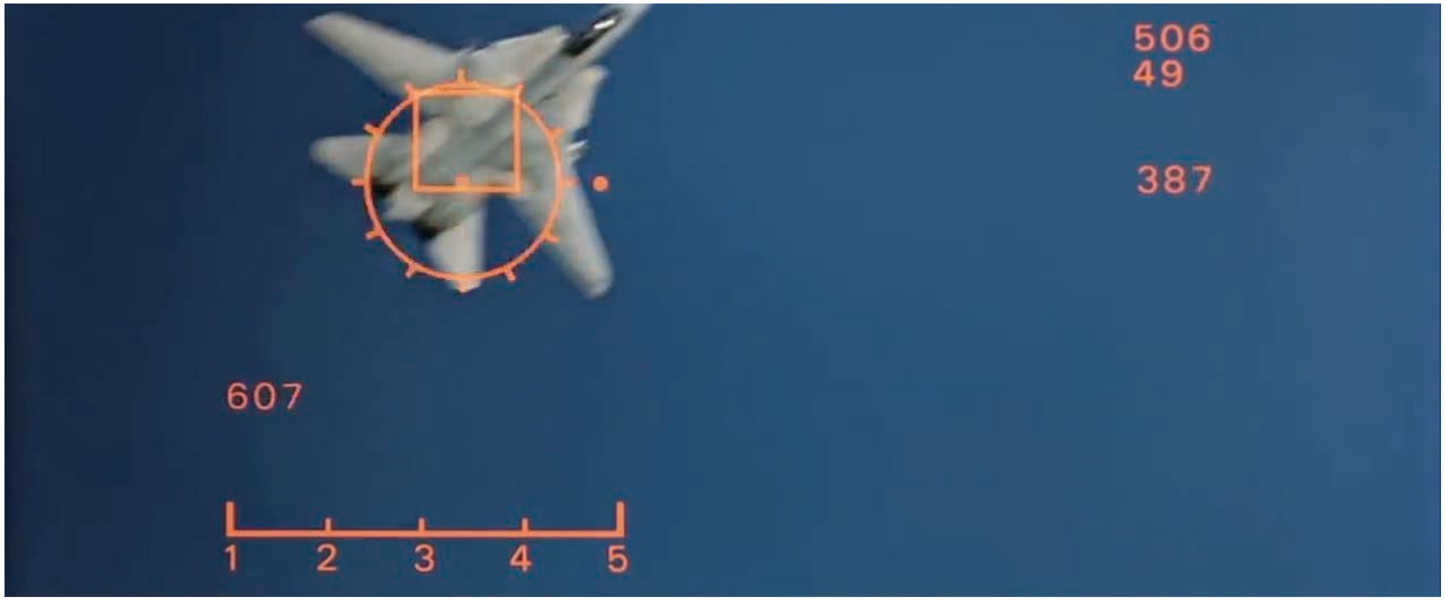
SfM: Structure from Motion

- Tracked Points gives correspondences





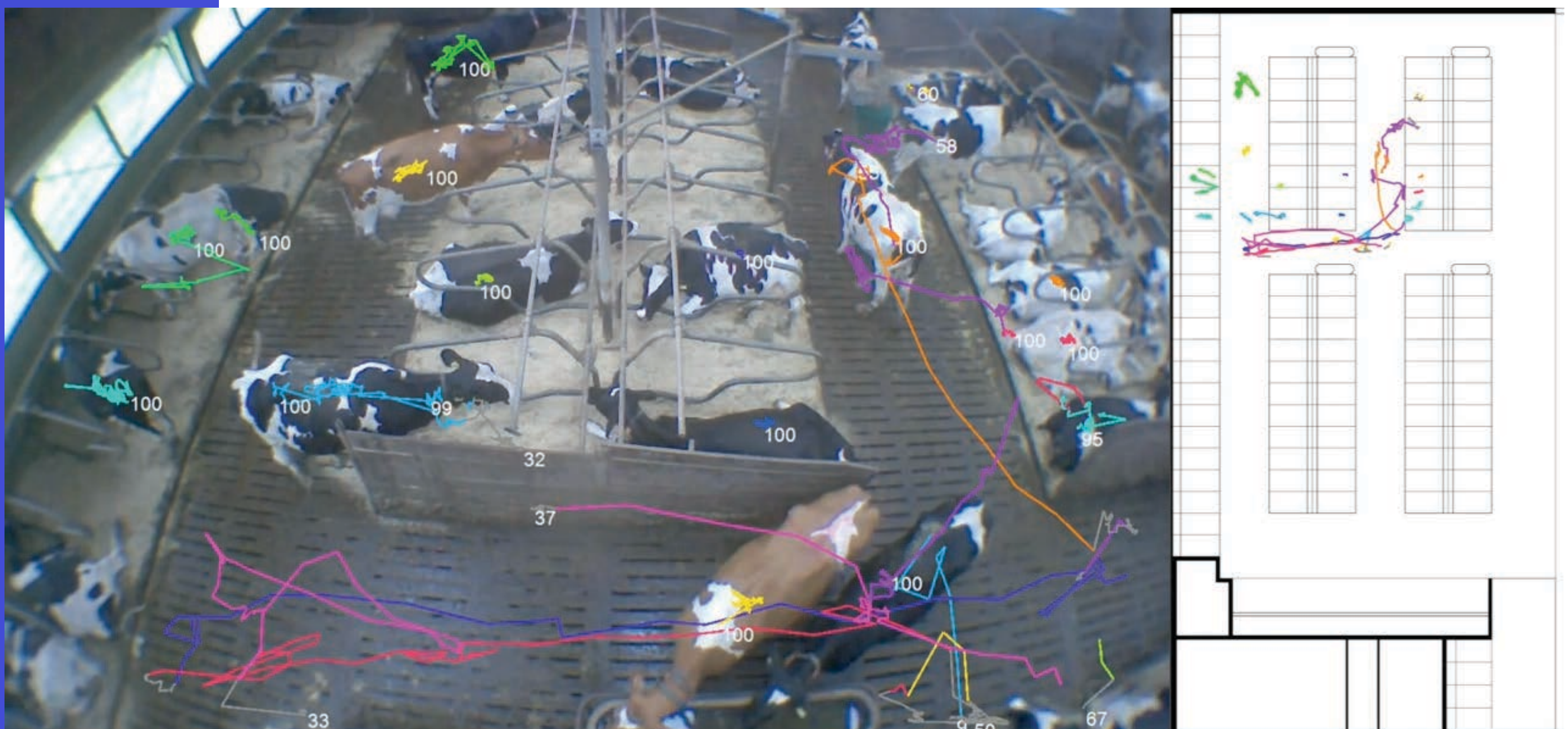
Defense



"Top Gun"

Computer Vision

Of course, "very importantly" The Cow Tracker



Applications

- Structure-from-Motion
- Autonomous Driving
- Gesture/Action Recognition
- Augmented Reality
- Navigation
- Safety and Security
- Medical Targeting / Guidance
- Motion Compensation
- …

You will be able to:

1. Determine applications of tracking and identify problems solvable by tracking
2. Analyze what methods could work in a practical scenario / situation
3. Assess potential limitations / pitfalls of particular approaches and scenarios
4. **Propose an optimal tracking solution**

<u>How will we get there:</u>

- (some) common tracking methods
- Few particular keywords & implementation
- What not: details of all individual implementations; cf. “how to google”

Think about

Q. What tracking method would you use in each following application scenario?

What limitations you may expect?

Task: “Discuss each in groups”

App1. Safety: In a lumbar mill, you wish to use CV to stop the blade if a hand reaches nearby.

App2. Medical: You wish to track the ultrasound probe, to relate images in 3D space.

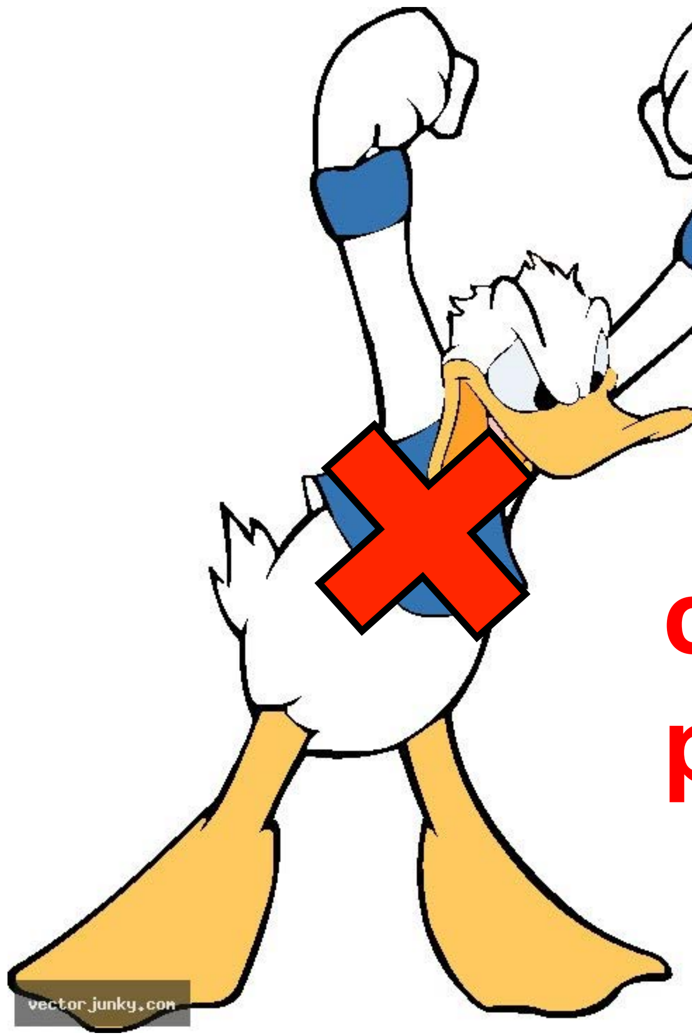
App3. Autonomous driving: Tracking other nearby vehicles to adjust speed and course.

(AppX. Your favourite tracking app)

Computer
Vision

What to track?

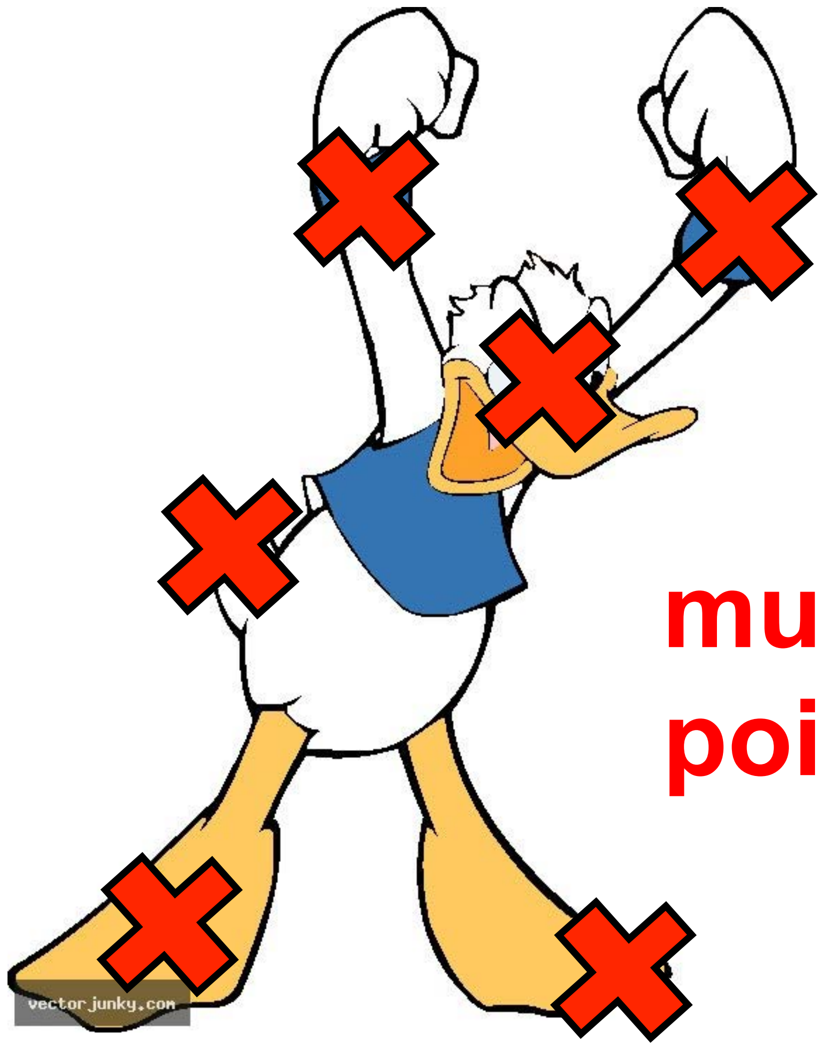
What to track?



center point

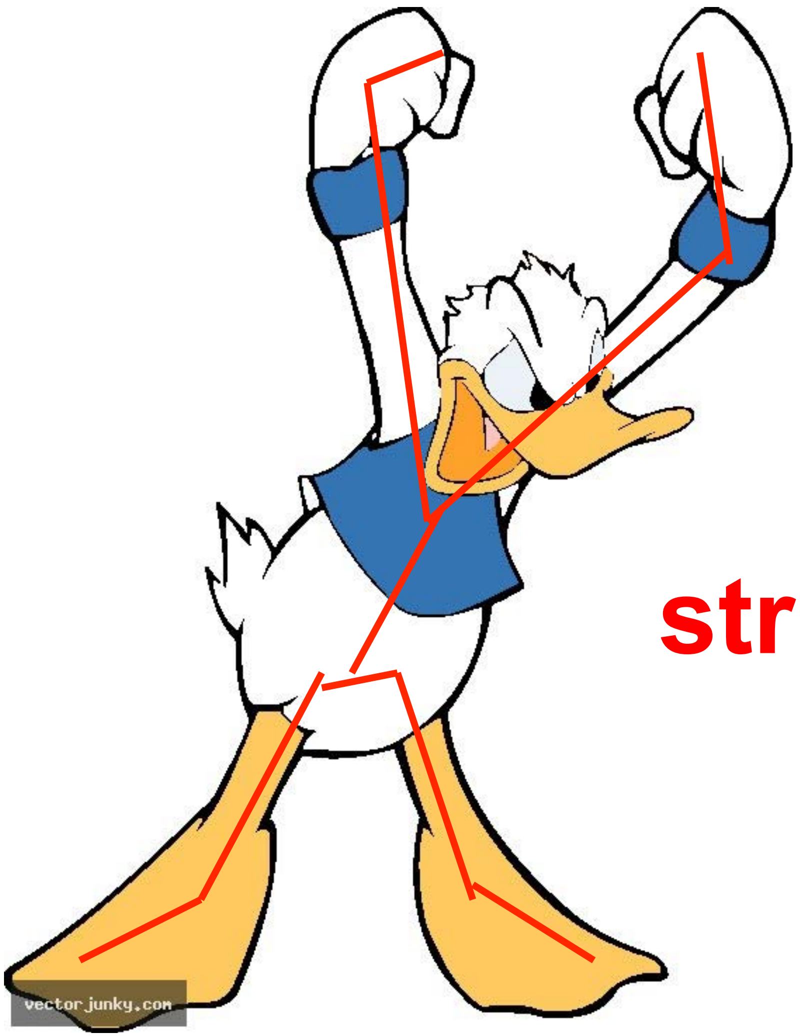
Computer Vision

What to track?



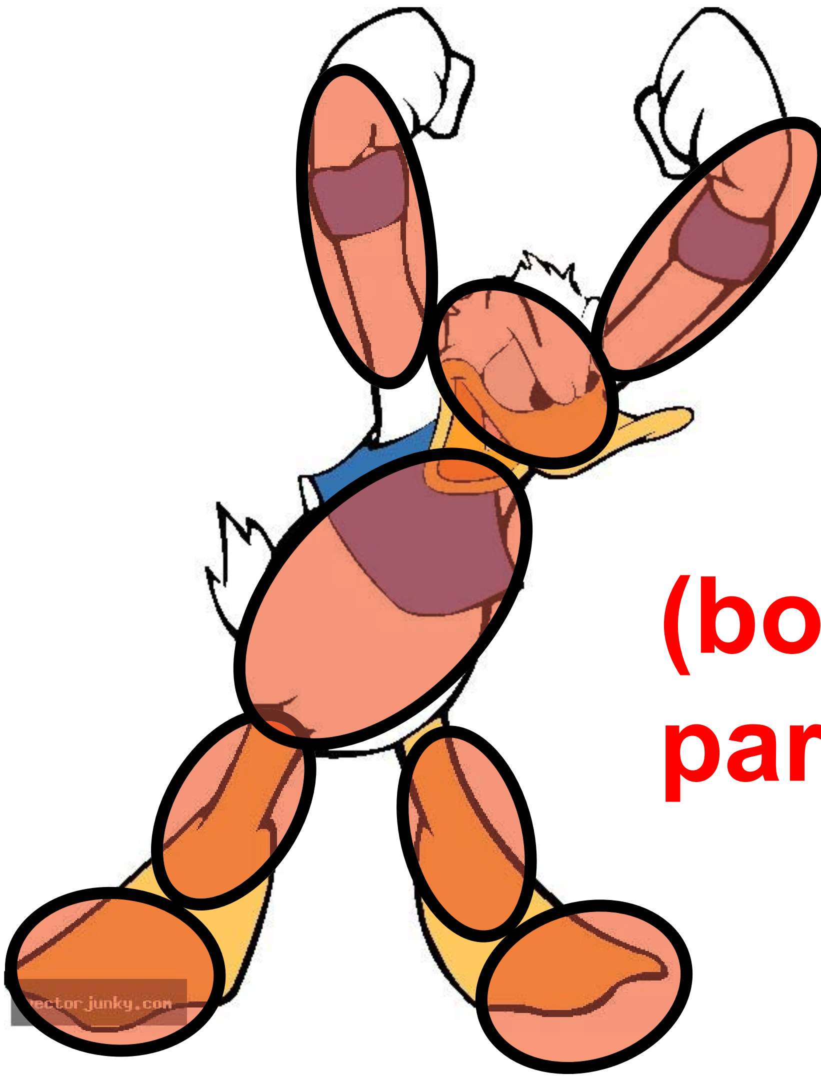
multiple points

What to track?



structure

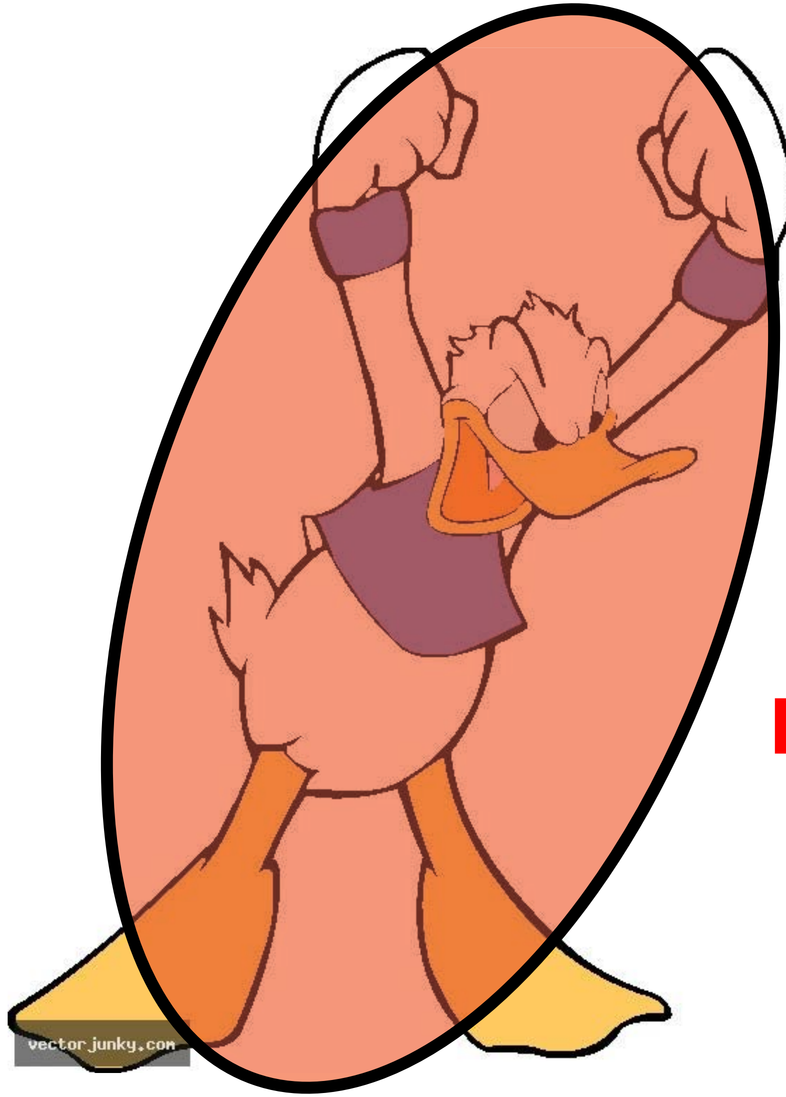
What to track?



(body) parts

Computer Vision

What to track?



region

Computer Vision

What to track?

Approaches

(i) Feature tracking

generic

corners, blob/contours, regions, …

(ii) Model-based tracking

application-specific

face, human body, …

Tracking Requirements

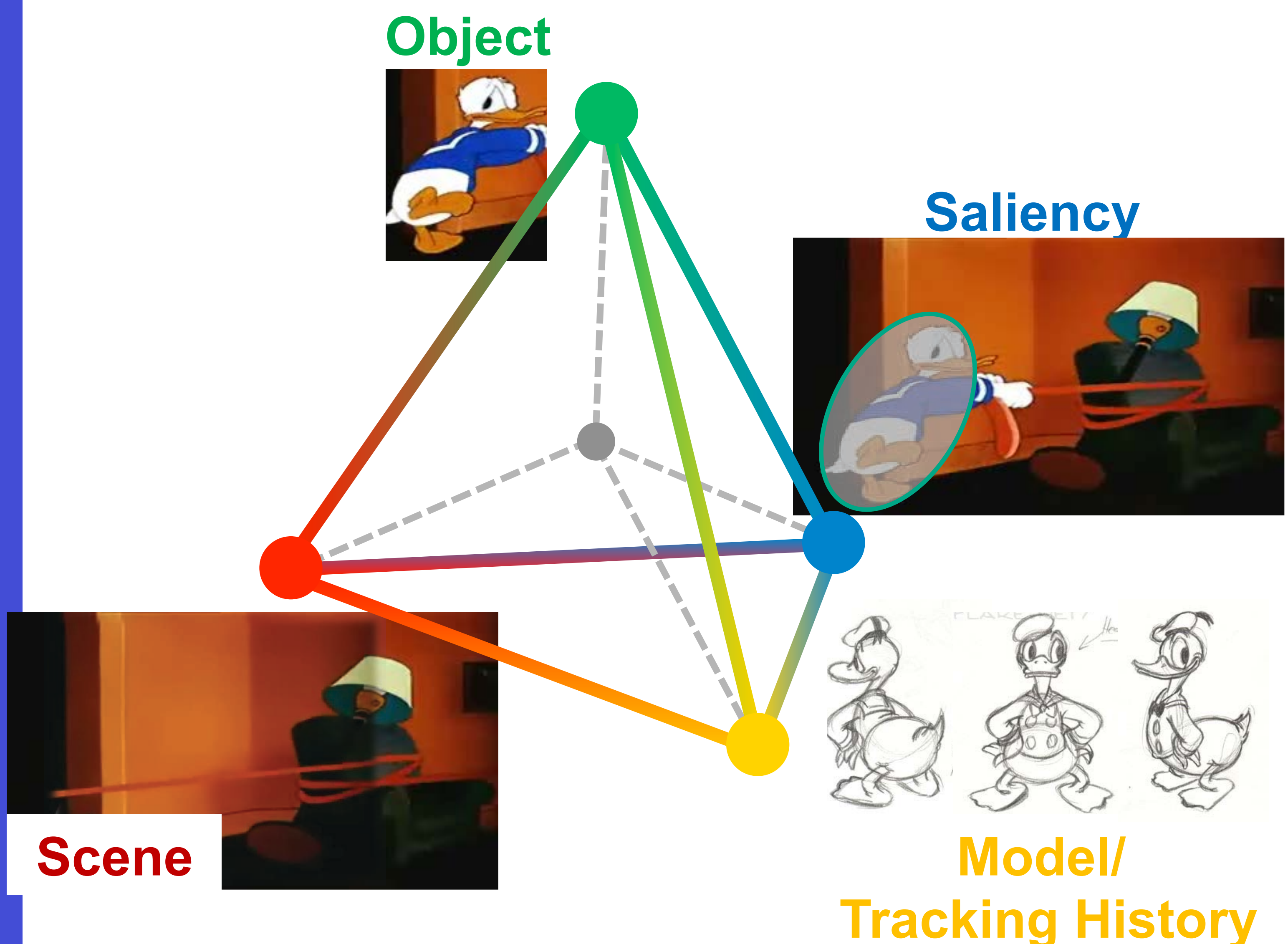
- Strongly depends on the **application**!

Robust, Accurate, Fast,…

- Constrain the tracking task!

Information about the object, dynamics, …

Tracking Cues

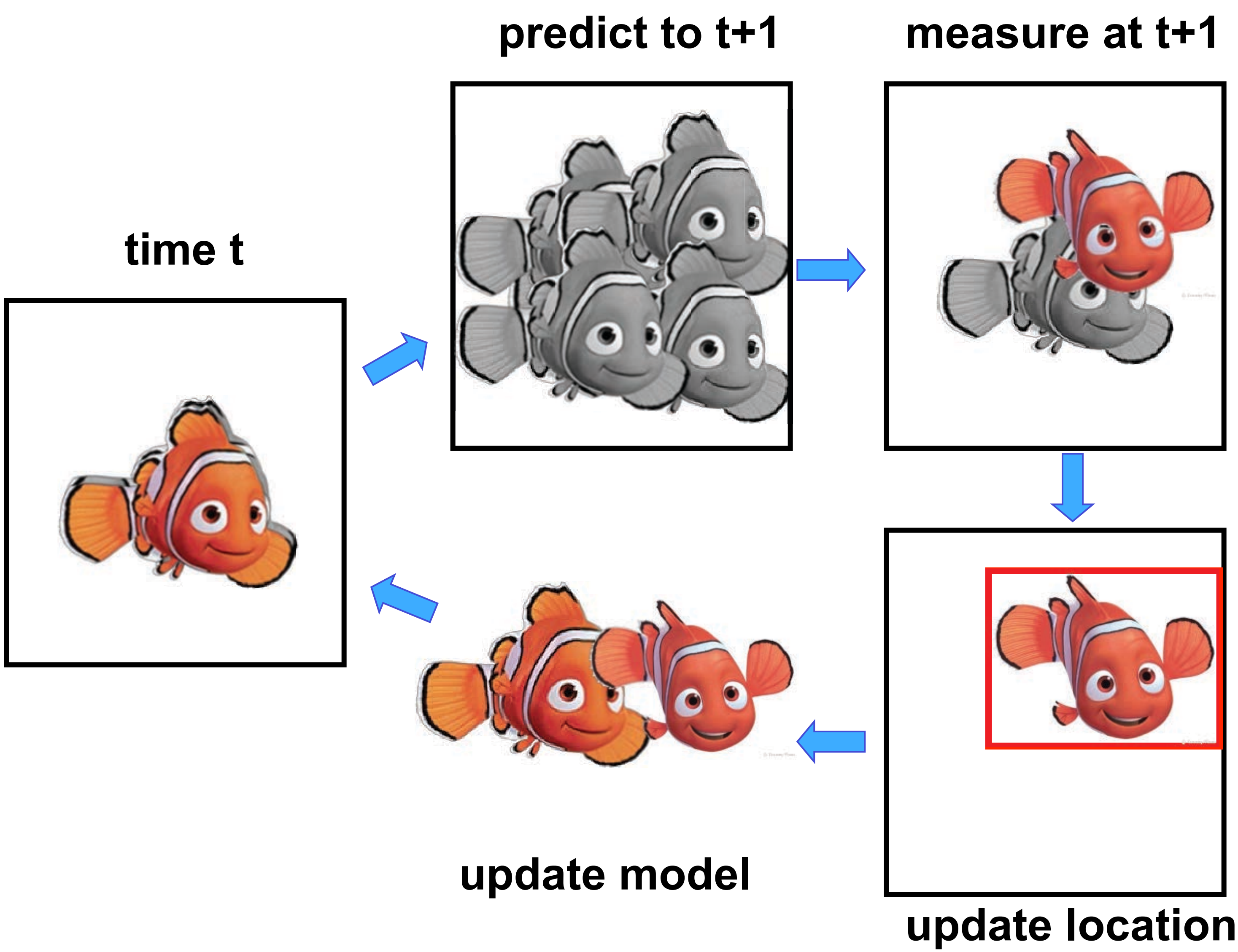


Motion as a Cue

Motion as a Cue

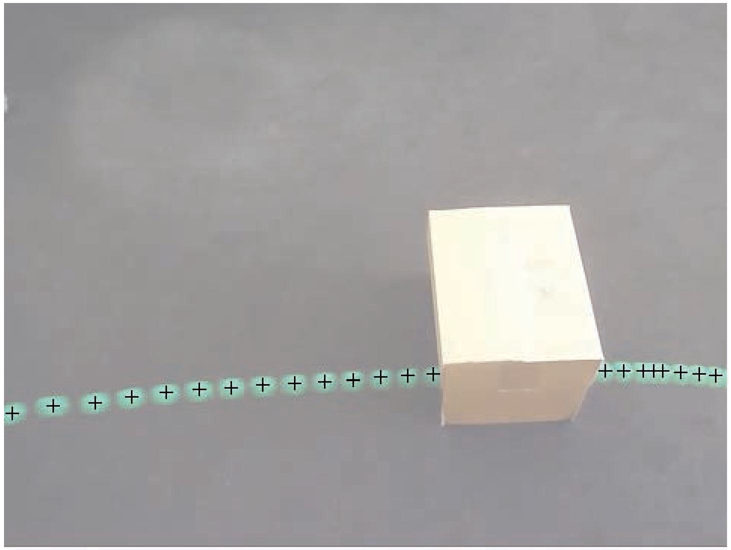
- Eye perceptive to temporal changes (gradients)
- "Event based camera"

General Tracking Loop



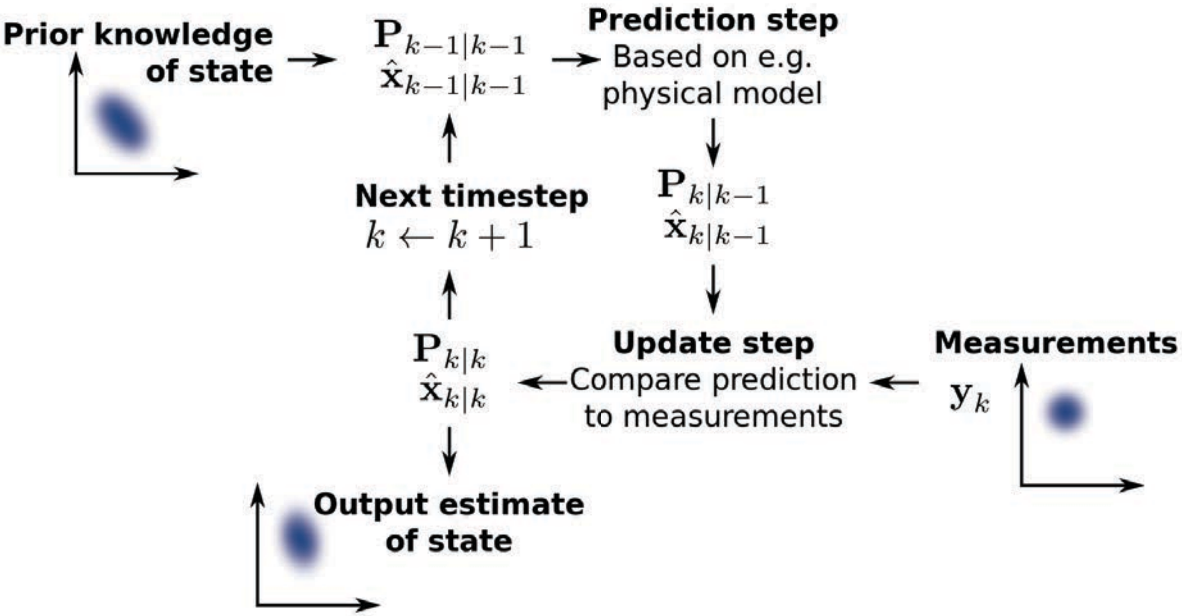
Trajectory
(Temporal Filtering)

Temporal Filtering/Predictions



- To predict location
- To reduce noise
- To disambiguate multiple objects

<u>Kalman Filtering</u>



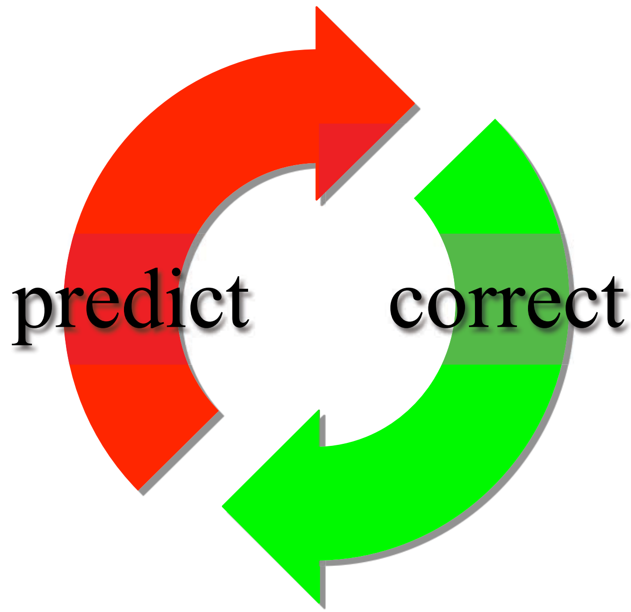
An ETH Legacy

http://www.ethlife.ethz.ch/archive_articles/091008_kalman_per

08.10.2009
<< Rudolf Kalman, ETH-Zurich emeritus professor of mathematics, is awarded the National Medal of Science by Barack Obama – one of the highest accolades for researchers in the USA.

In January 2008, Hungarian-born Kalman received the Charles Draper Prize, which is regarded as the "Nobel Prize" of the engineering world. >>

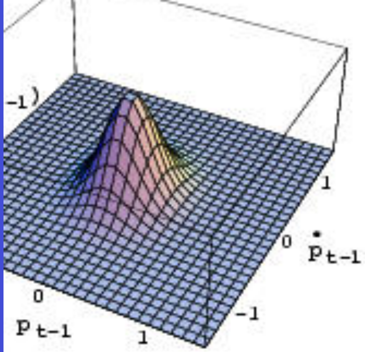
Steps of Tracking

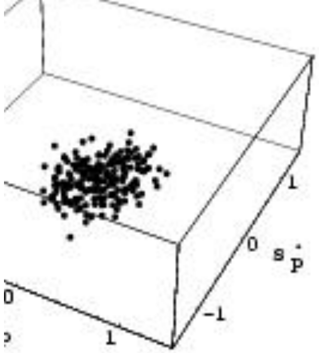


- Recap: Particle filtering
  - Tracking can be seen as the process of propagating the posterior distribution of state given measurements across time.

Computer Vision

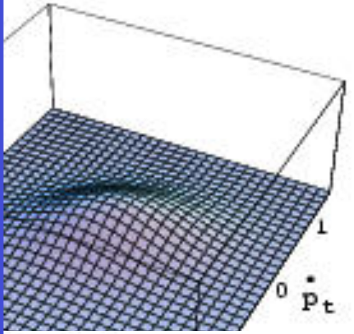
Particle Filter

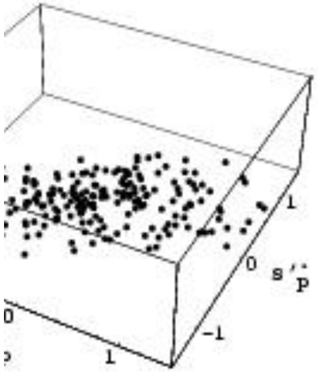




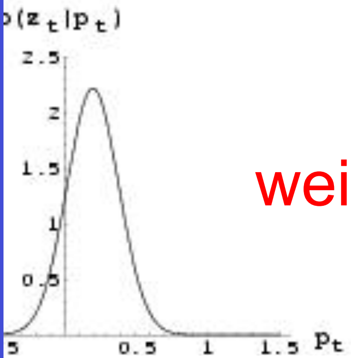
$$p(p_{t-1}, \dot{p}_{t-1} \mid z_{t-1})$$

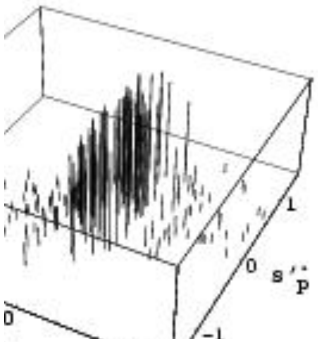
prediction





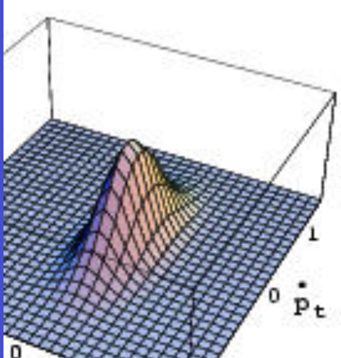
$$p(p_t, \dot{p}_t \mid z_{t-1})$$

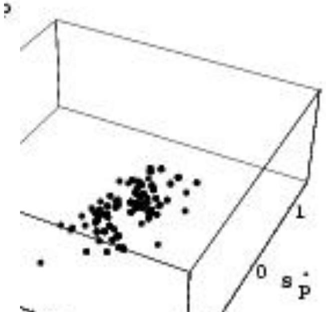




weighing with $\boxed{p(z_t \mid p_t)}$

update





$$p(p_t, \dot{p}_t \mid z_t)$$

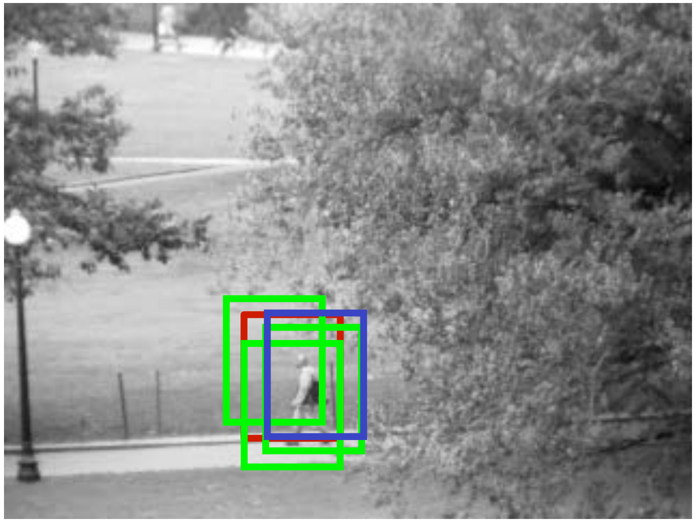
C O N D E N S A T I O N

Computer Vision

Traditional/Simple Tracking

t=1

initialization



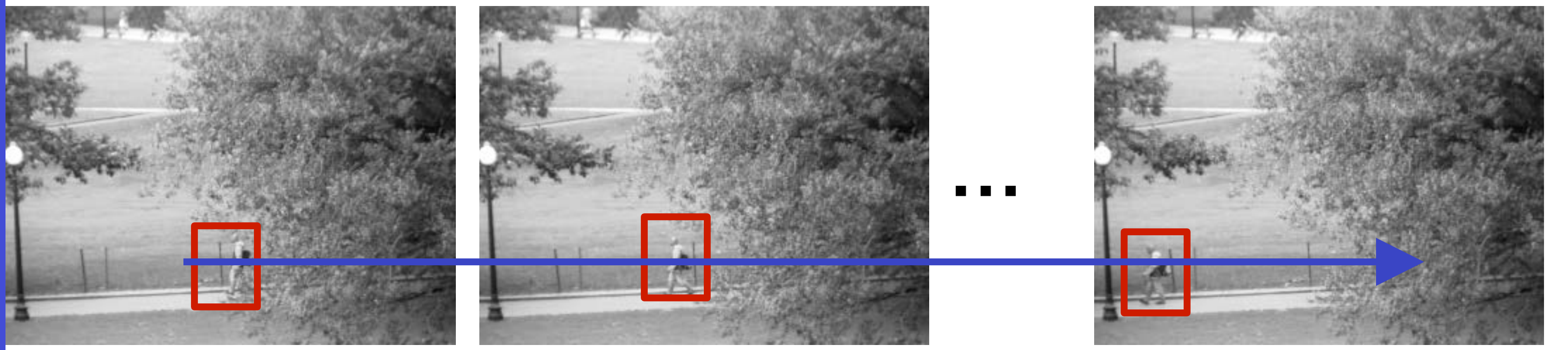
t=2

position in prev. frame

candidate new positions (e.g., dynamics)

best new position (e.g., max color similarity)

Tracking-by-Detection



detect object(s) independently in each frame

associate detections over time into *tracks*

Computer Vision

Outline

Feature

- Region Tracking
- Point Tracking
- Template Tracking

Model

- Tracking-by-Detection
  - a specific target
  - object class
- Model-based Body Articulation
- On-line Learning

- Misc (preventing drift, context, issues)

Computer Vision

Region Tracking

(and Mean Shift Algorithm)

Computer Vision

Background Modeling

For known (fixed) background, simply save it and subtract from each frame

Input

-

Background Model

Large moving blobs are the objects (foreground)

Sources of errors, e.g.:
* same color as backg
* lighting changes
* camera noise/motion
* occlusion

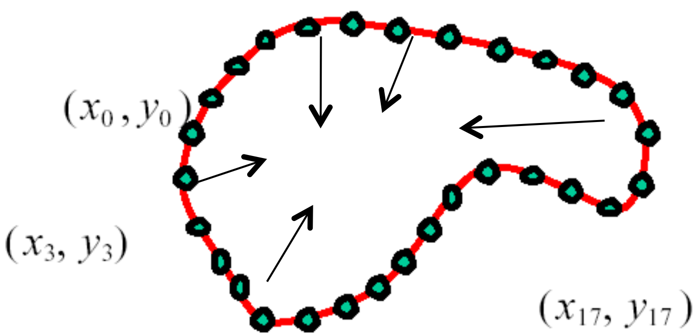
…

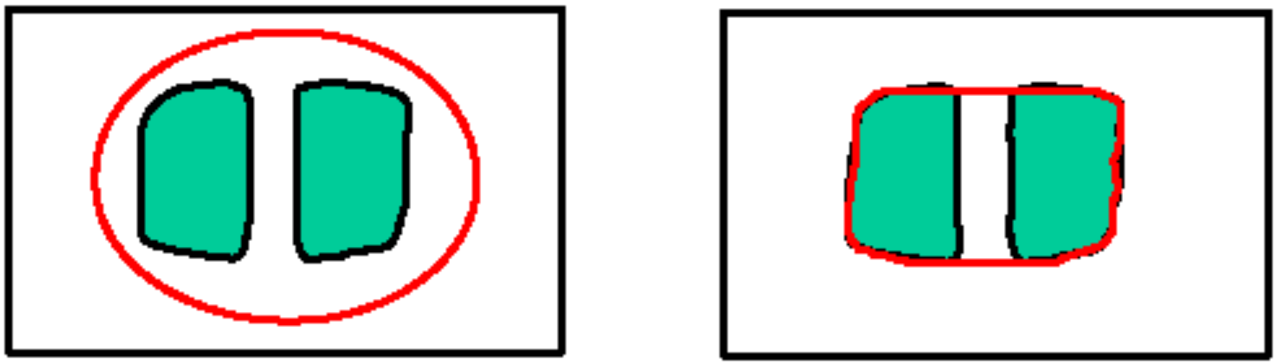
Noise must be filtered, to extract the object

Computer Vision

Deformable models

- One option: Fit deformable curves





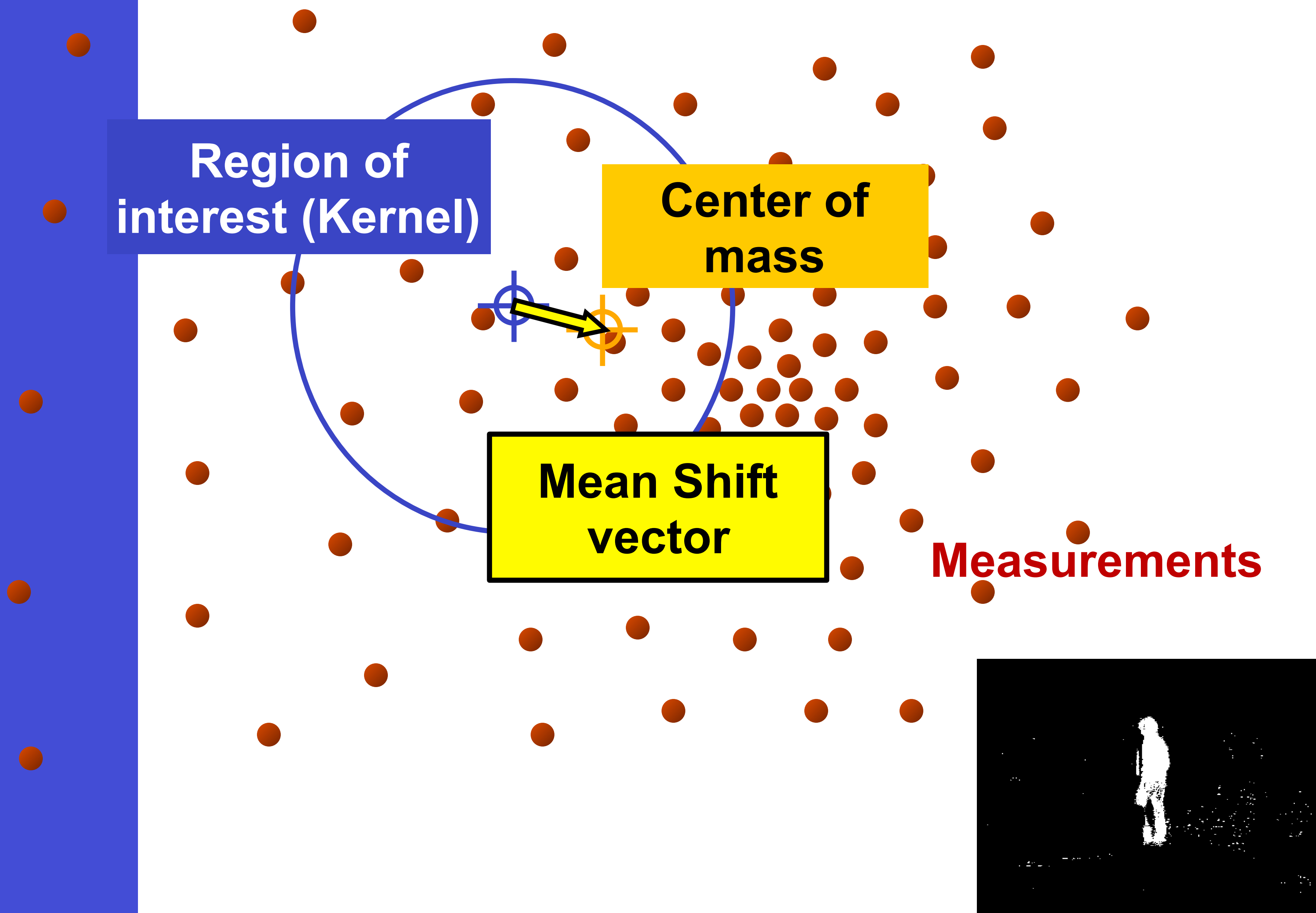
Mean Shift Method

- Mean Shift Tracking (general description) Maximize similarity between tracked and target regions through evolution towards higher density in a parameter space
- Can be used to find the object from background modeling, by assuming that the object is formed of a large group of densely located pixels (in contrast to noise as fewer scattered foreground pixels)
- A mean (center) location is iteratively updated by moving it to the *centroid* of pixels within a chosen radius

[Comaniciu and Meer, ICCV'99]

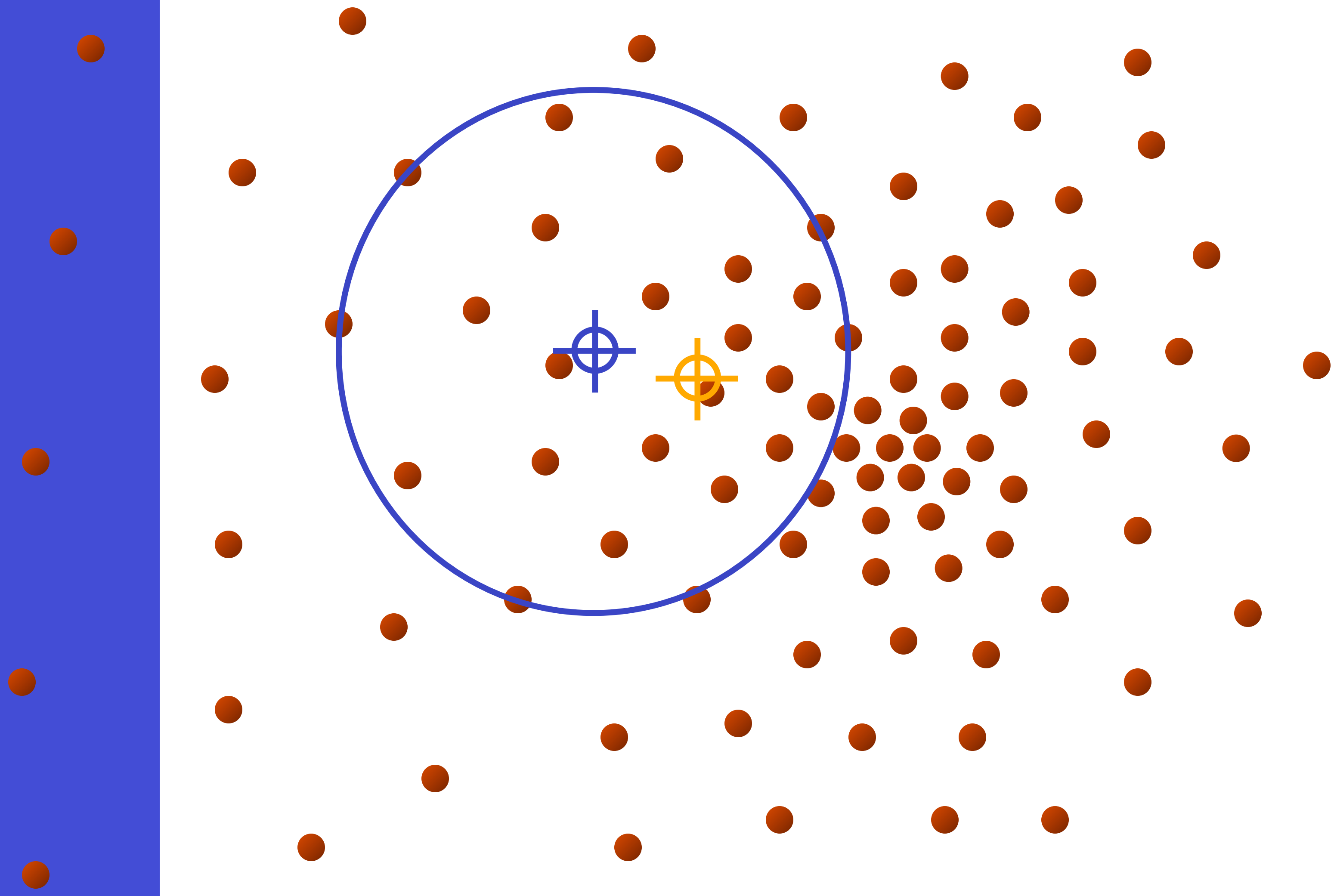
Computer Vision

Meanshift Tracking



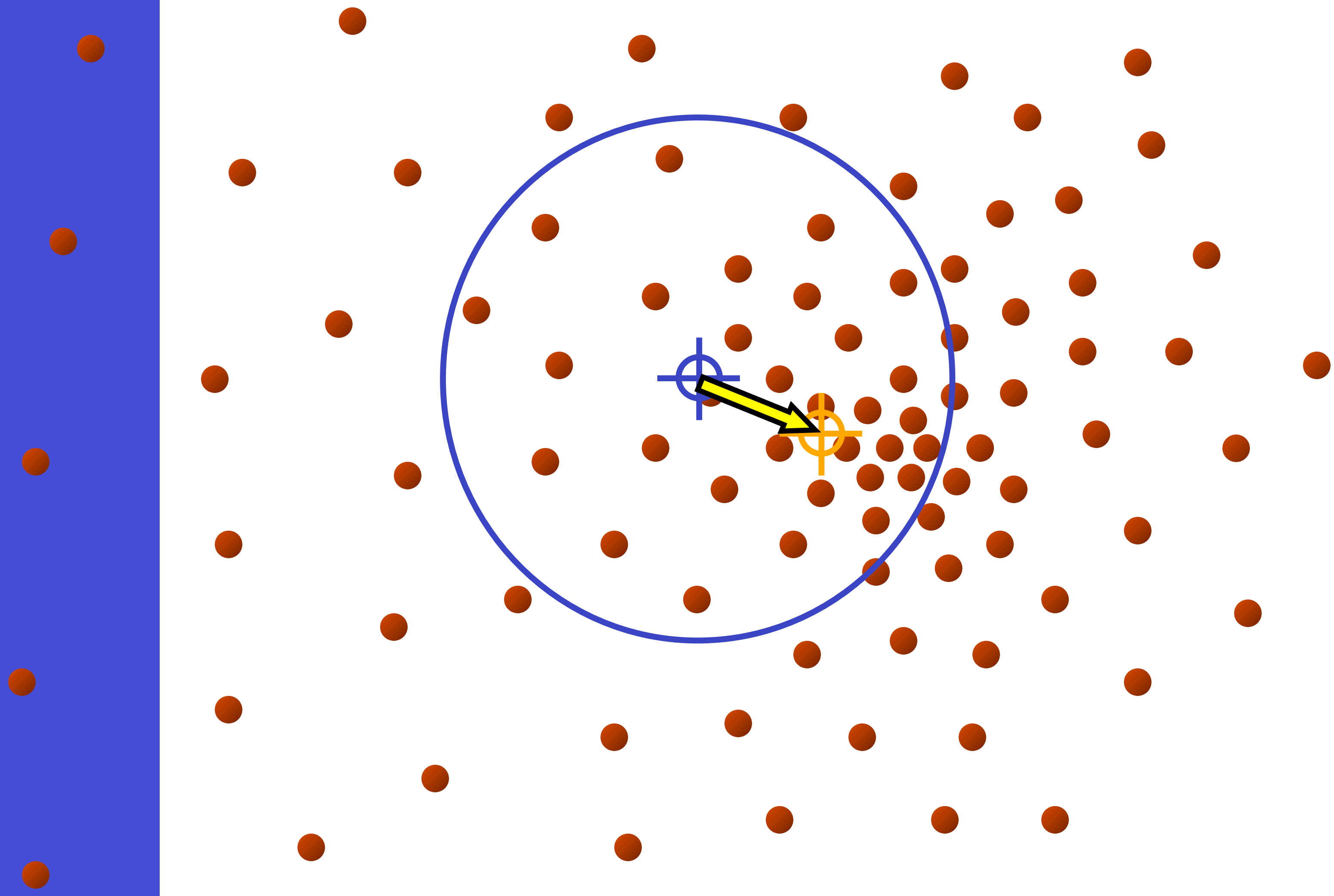
Computer Vision

Intuitive Description

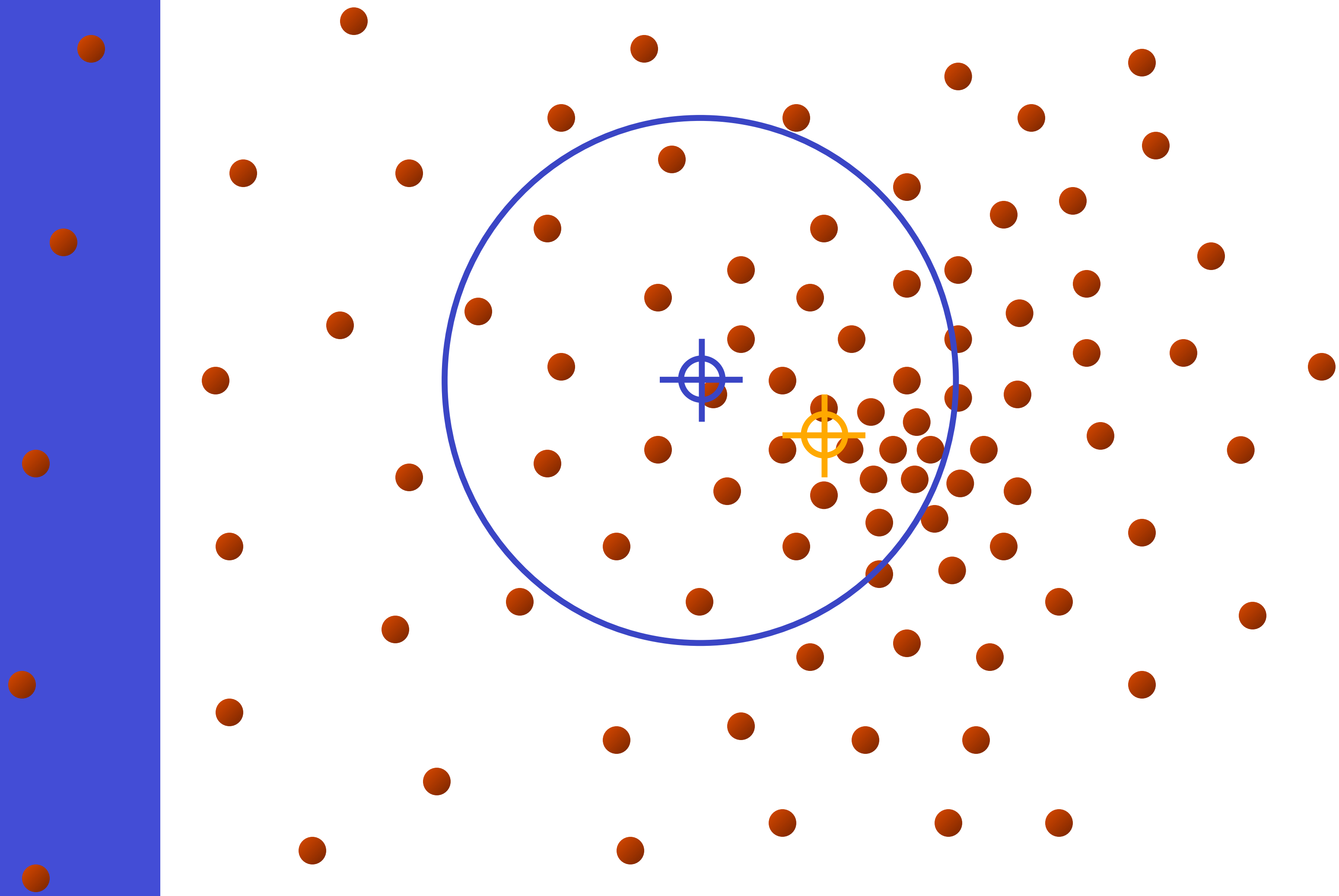


Computer Vision

Intuitive Description

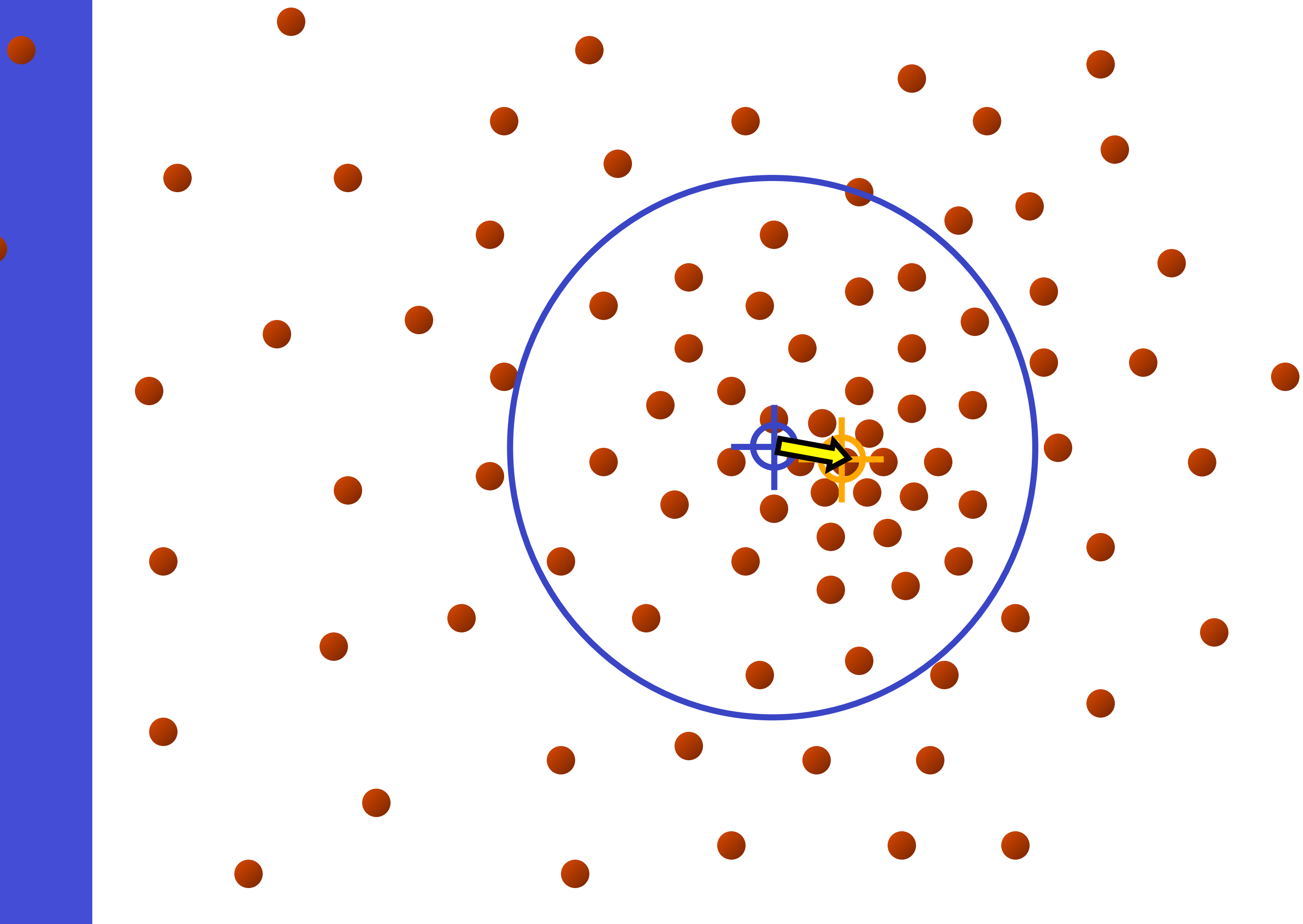


Intuitive Description



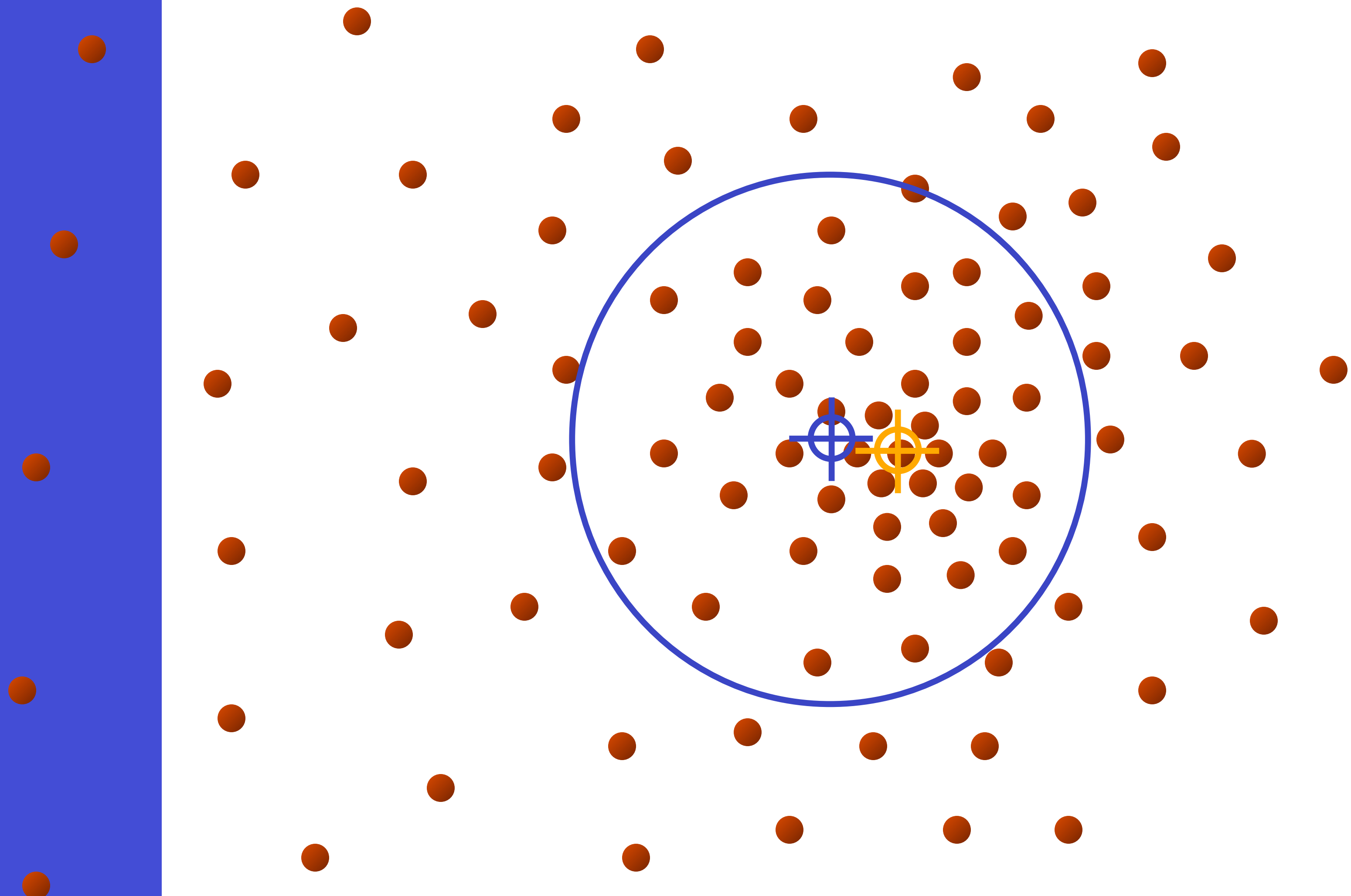
Computer Vision

Intuitive Description



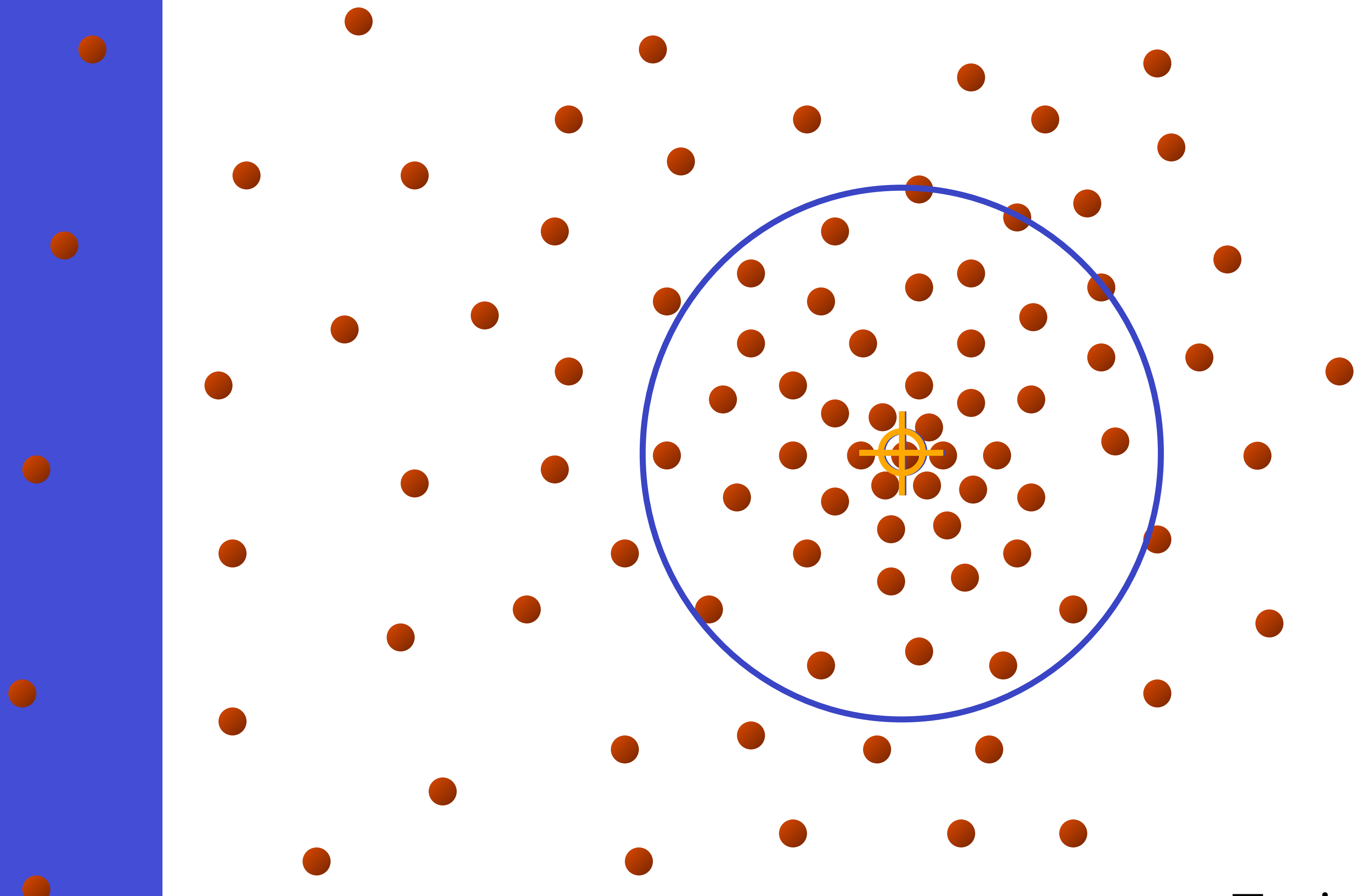
Computer Vision

Intuitive Description



Computer Vision

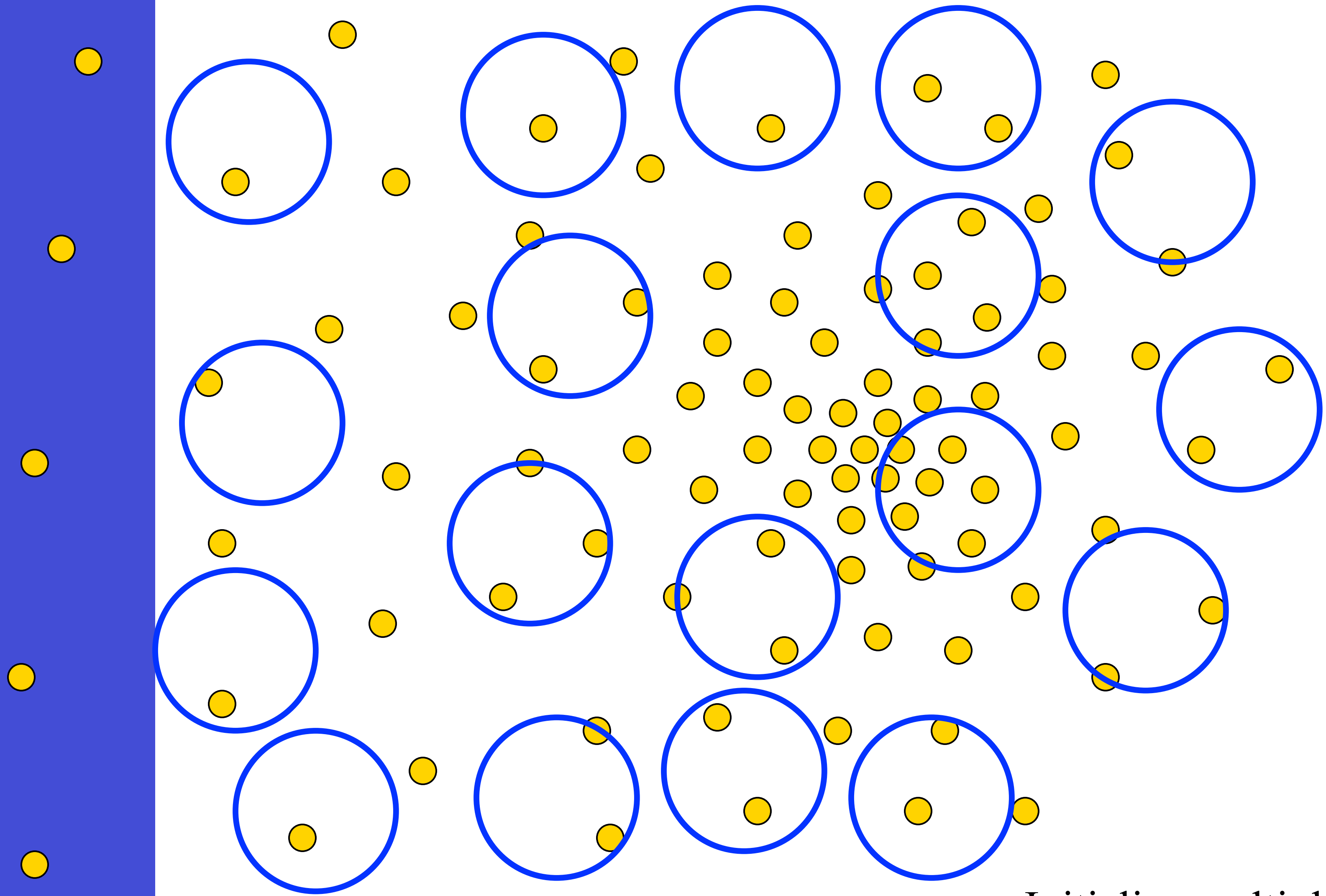
Intuitive Description



Typically this search only takes a few iterations

Computer Vision

Intuitive Description



Initialize multiple means and pick the location where many converges

Computer Vision

Example: Safety Monitoring

Computer Vision

Outline

Feature

- Region Tracking (and Mean Shift Algorithm)
- Point Tracking
- Template Tracking

Model

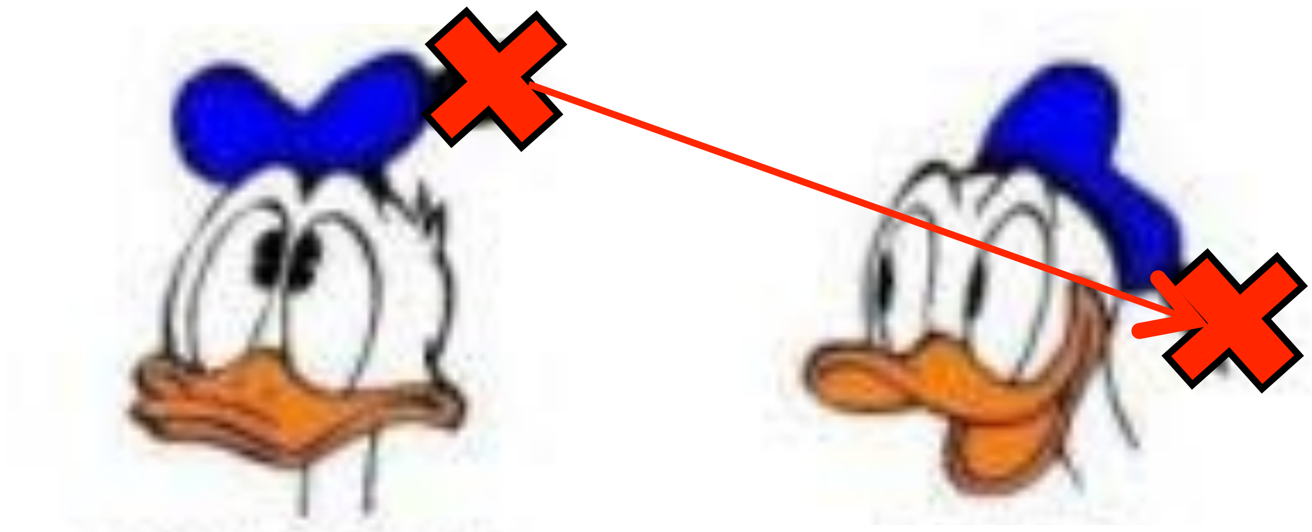
- Tracking-by-Detection
  - a specific target
  - object class
- Model-based Body Articulation
- On-line Learning

- Misc (preventing drift, context, issues)

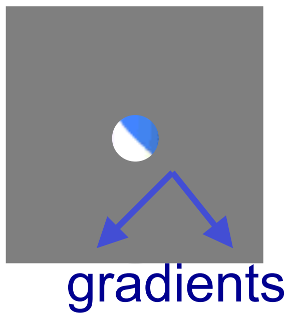
Computer Vision

Point Tracking
(and Aperture Problem)

Estimate Optimal Transformation



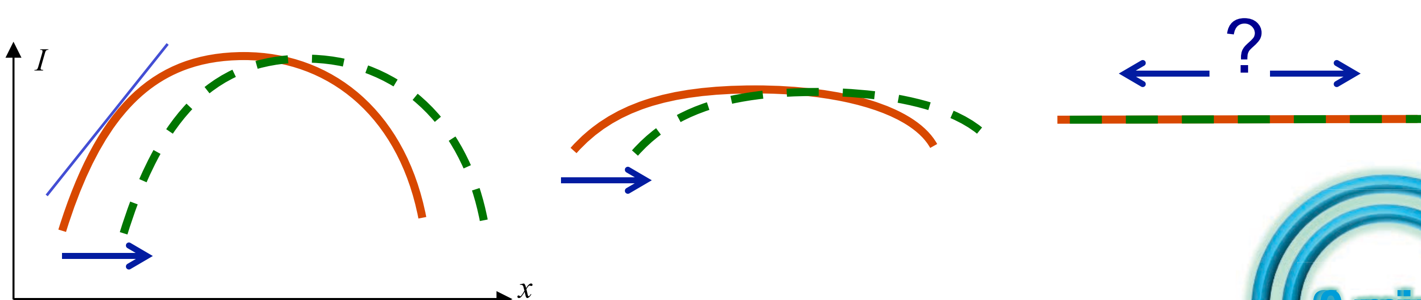
When can we (not) estimate motion?



Q1. Which direction is the pattern behind the circular hole moving in physical space?

a) ↙ b) ← c) ↓ d) ?

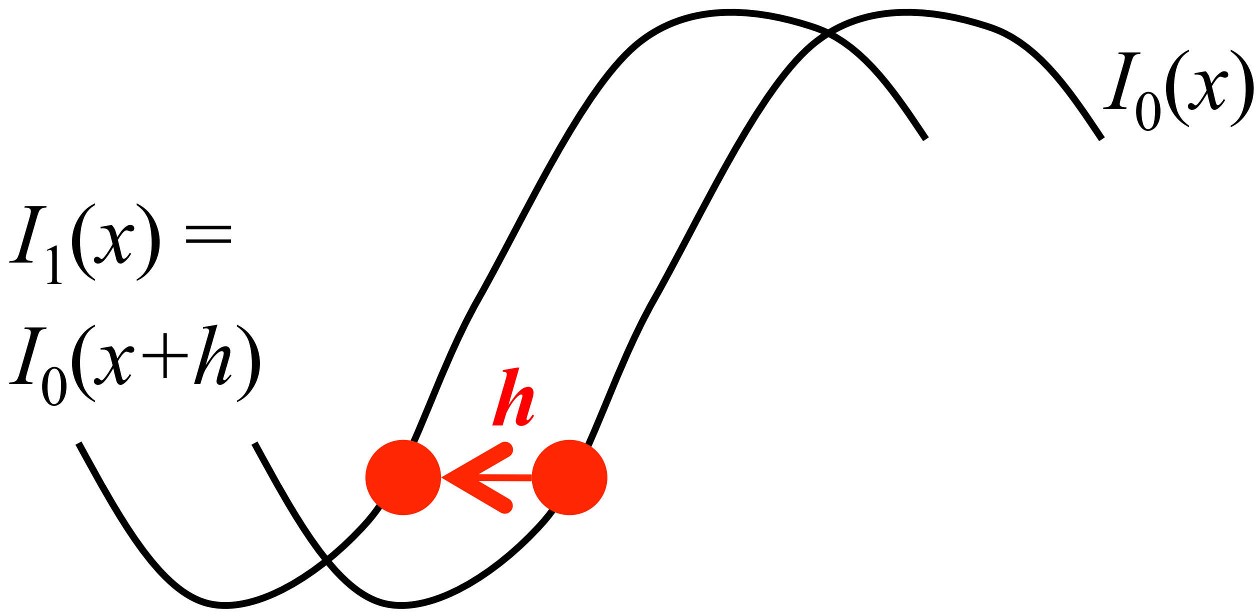
Q2. Motion in 1D: What mathematical property of curves make it impossible to determine the direction of motion from **red** to **green** line in the last case?



Q3. What is common between Q1 & Q2?

Computer Vision

Sum of Squared Differences



$$E(h) = [I_0(x+h) - I_1(x)]^2$$

Displacement

$$E(h) = [\ I_0(x+h) - I_1(x)\ ]^2$$

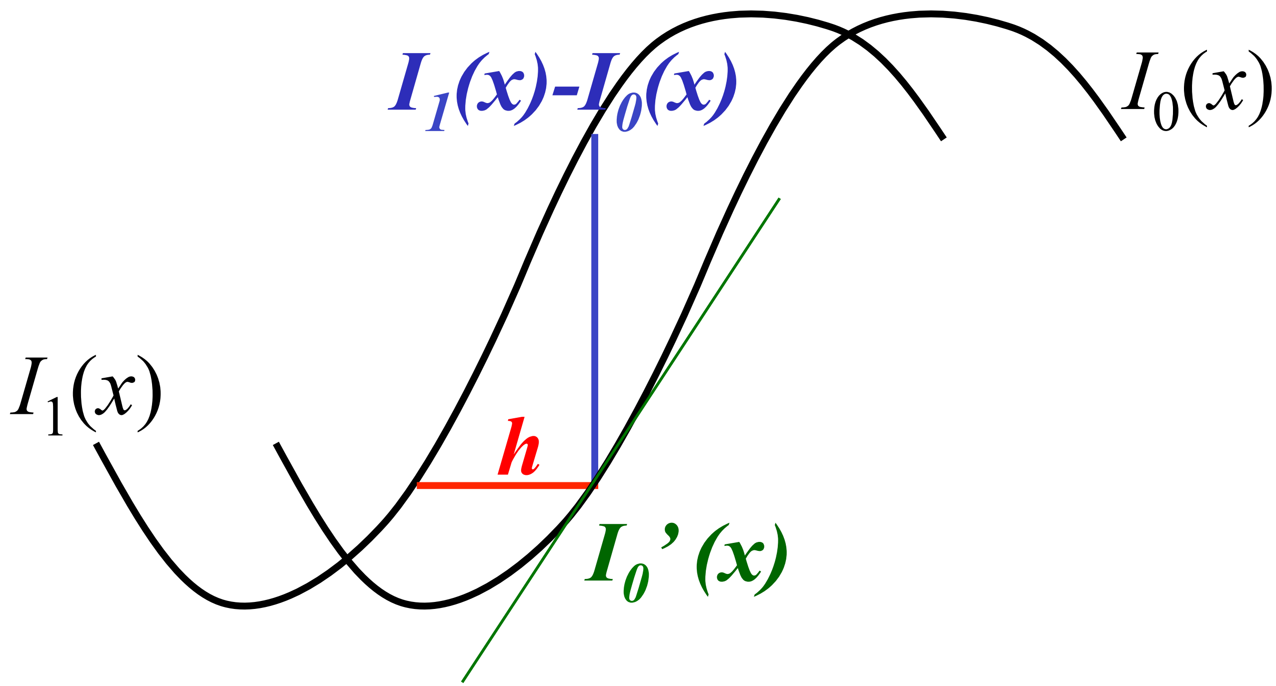
$$E(h) \approx [\ I_0(x) + hI_0'(x) - I_1(x)\ ]^2$$

$$\frac{\partial E}{\partial h} \approx 2\ I_0'(x)\ [\ I_0(x) + hI_0'(x) - I_1(x)\ ] = 0$$

$$h \approx \frac{I_1(x) - I_0(x)}{I_0'(x)}$$

Computer Vision

Intuition

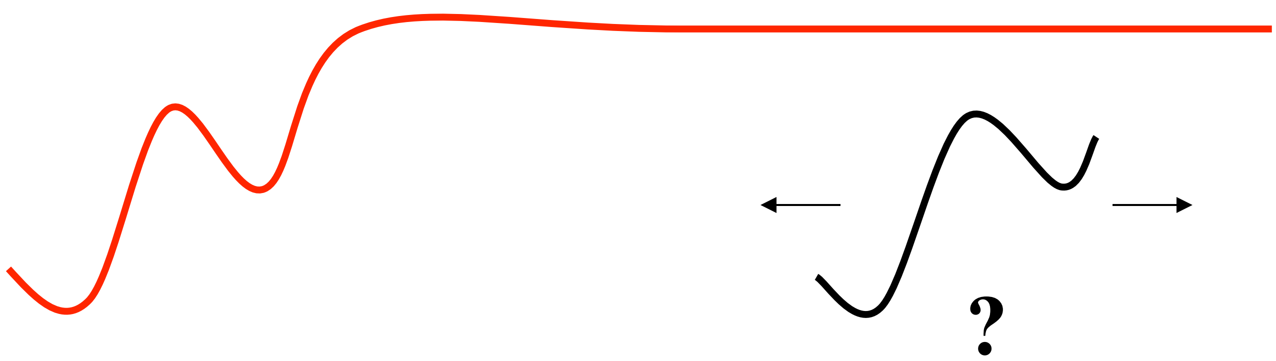


$$h \approx \frac{I_1(x) - I_0(x)}{I_0'(x)}$$

Computer Vision

Problem 1: Zero Gradient

$$h \approx \frac{I_1(x) - I_0(x)}{I_0'(x)}$$

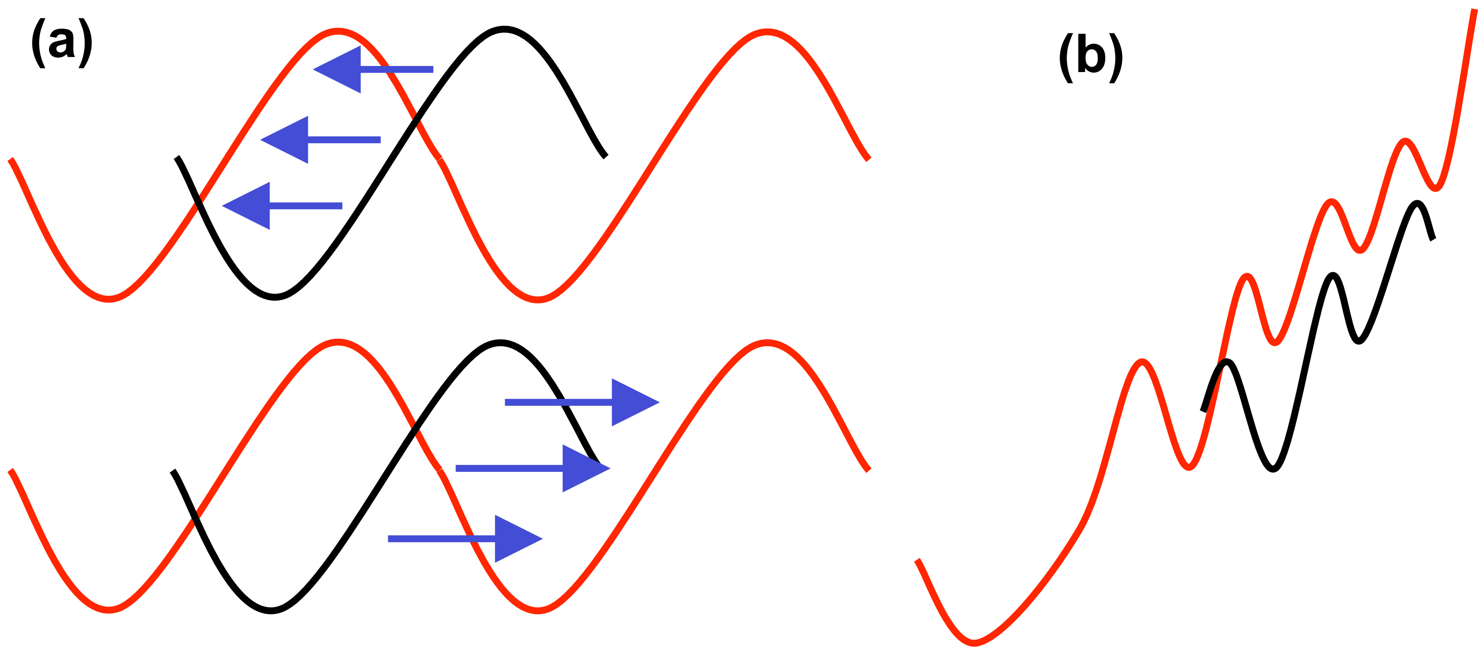


Problem 1: “Aperture problem”

- For tracking to be well defined, nonzero gradients in all possible directions are needed
- If no gradient along one direction, we cannot determine relative motion in that axis

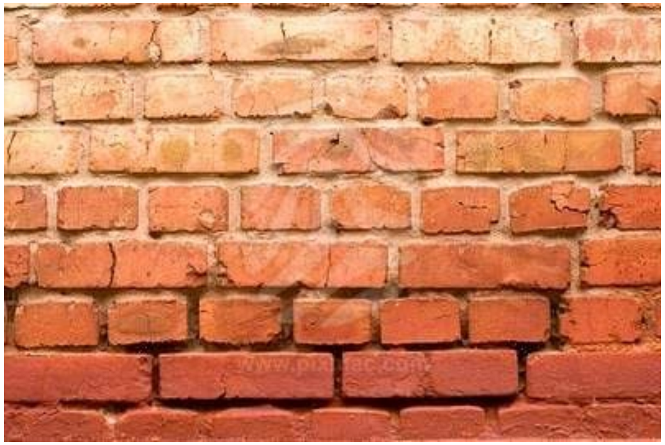
Computer Vision

Problem 2: Local Minima

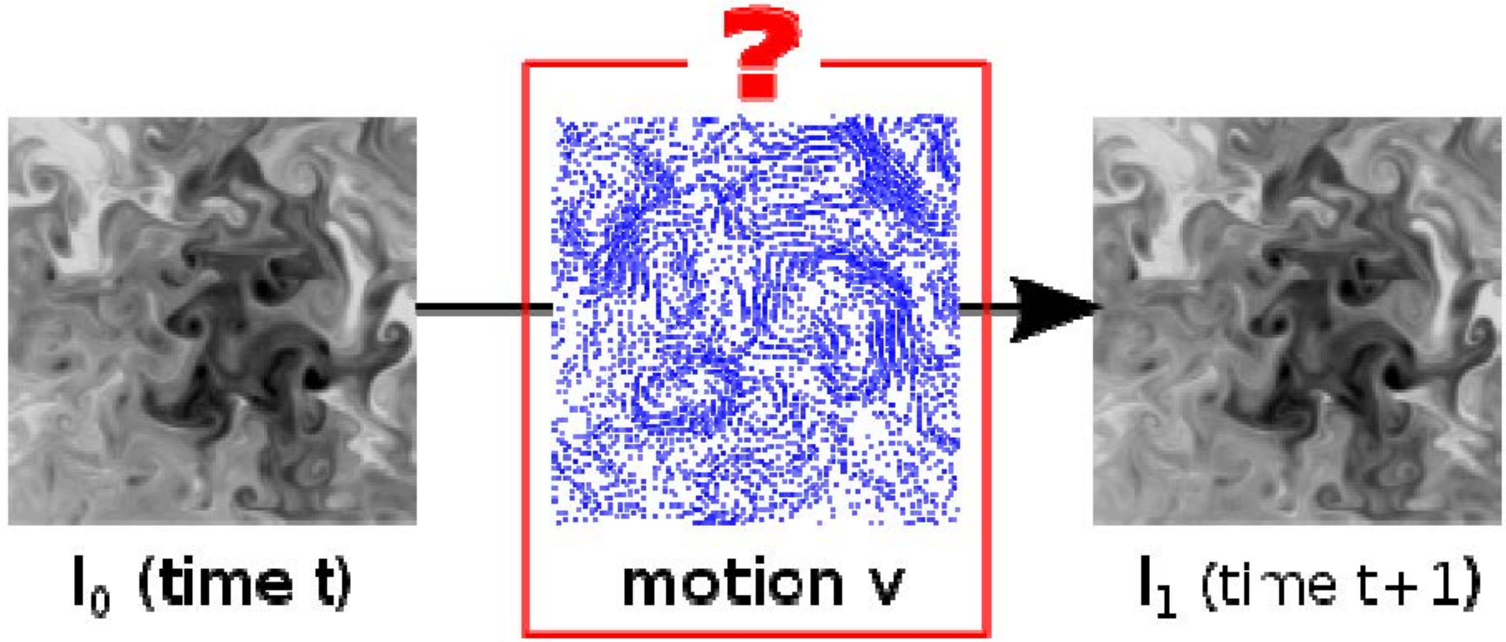


- Motion to closest minimum has to be assumed
- Indirect result: Frame-rate should be faster than motion of half-wavelength (Nyquist rate)
- Nonconvex regions may indicate multiple solns

Problem 2: Local Minima



Recall: Optical Flow in Motion Estimation



- OF recovers (smooth) motion everywhere
- Least-squares regularization: Horn-Schunk makes smooth spatial change assumption
- In contrast, tracking seeks a single motion!

Recall: Optical Flow

$$\boxed{I_x u + I_y v + I_t = 0}$$

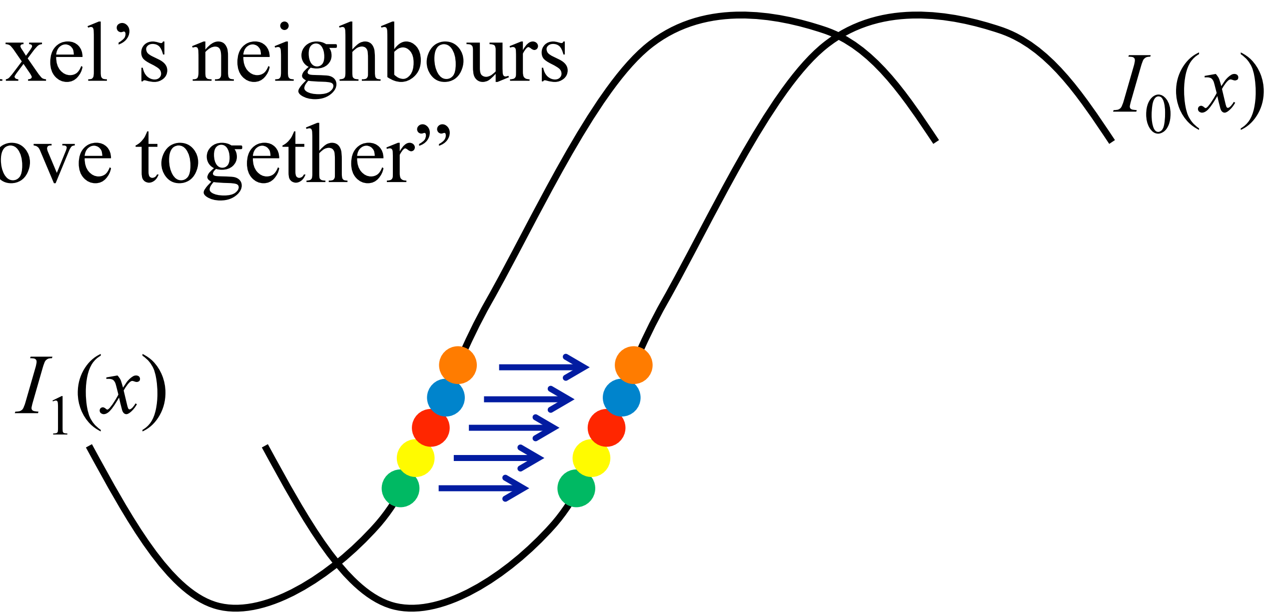
$$I_x = \frac{\partial I}{\partial x}, \quad I_y = \frac{\partial I}{\partial y}, \quad I_t = \frac{\partial I}{\partial t}$$

$$u = \frac{dx}{dt}, \quad v = \frac{dy}{dt}$$

1 equation in 2 unknowns

Treating Aperture Problem in Tracking

- Get additional info to constrain motion:
  - OF: Smoothly regularize in space
  - Tracking: Assume single motion for a region
- Spatial coherence constraint:
  "A pixel's neighbours all move together"



Least Squares Problem:
Single motion with multiple equations

$$\begin{bmatrix} I_x(\mathbf{p}_1) & I_y(\mathbf{p}_1) \\ I_x(\mathbf{p}_2) & I_y(\mathbf{p}_2) \\ \vdots & \vdots \\ I_x(\mathbf{p}_{25}) & I_y(\mathbf{p}_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p}_1) \\ I_t(\mathbf{p}_2) \\ \vdots \\ I_t(\mathbf{p}_{25}) \end{bmatrix}$$

Over determined System of Equations

$$\underset{25\mathrm{x}2}{A} \quad \underset{2\mathrm{x}1}{d} = \underset{25\mathrm{x}1}{b}$$

Pseudo Inverse

$$\underset{2\mathrm{x}2}{(A^T A)} \quad \underset{2\mathrm{x}1}{d} = \underset{2\mathrm{x}1}{A^T b}$$

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

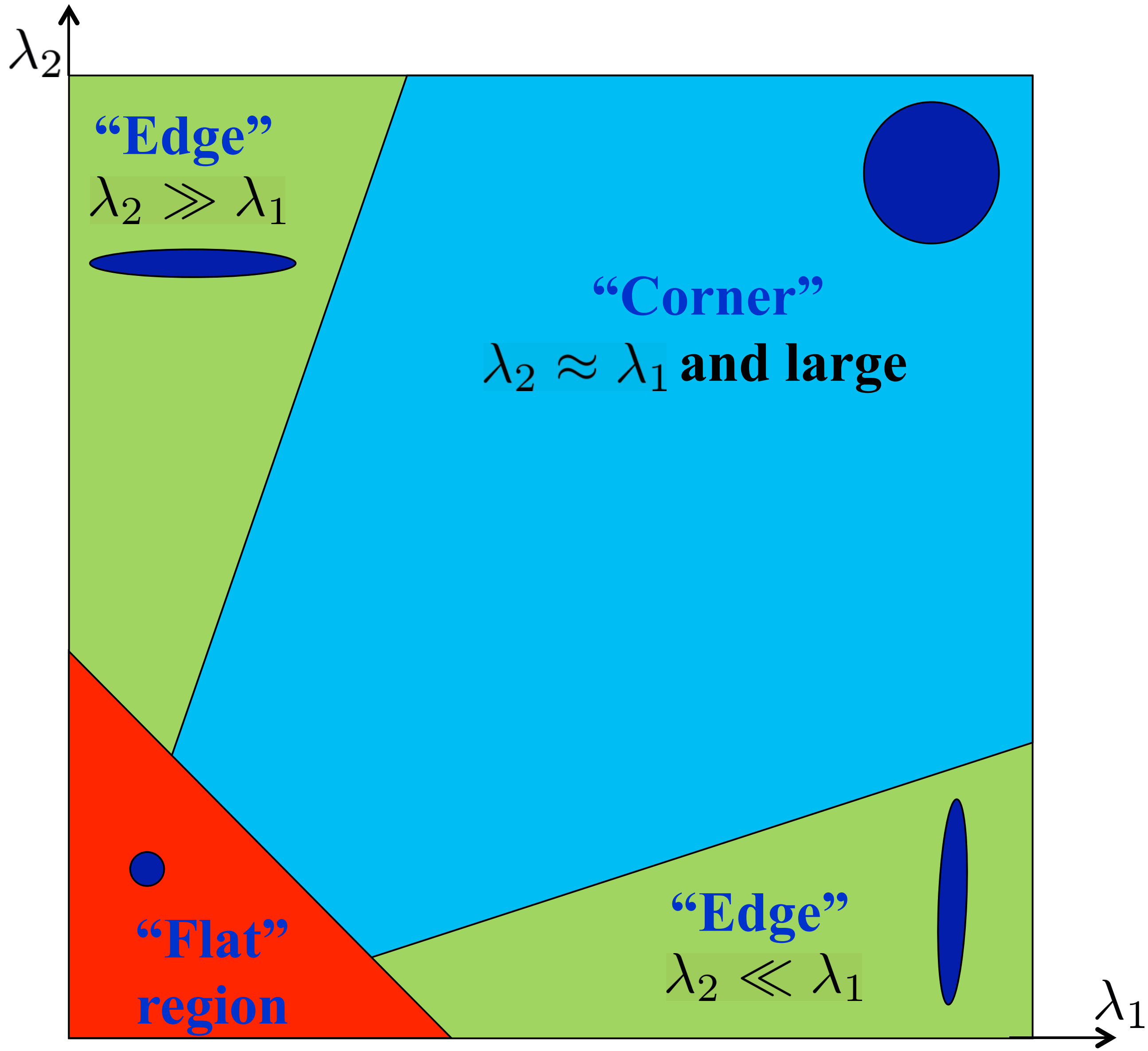
Eigenvectors of $A^T A$

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

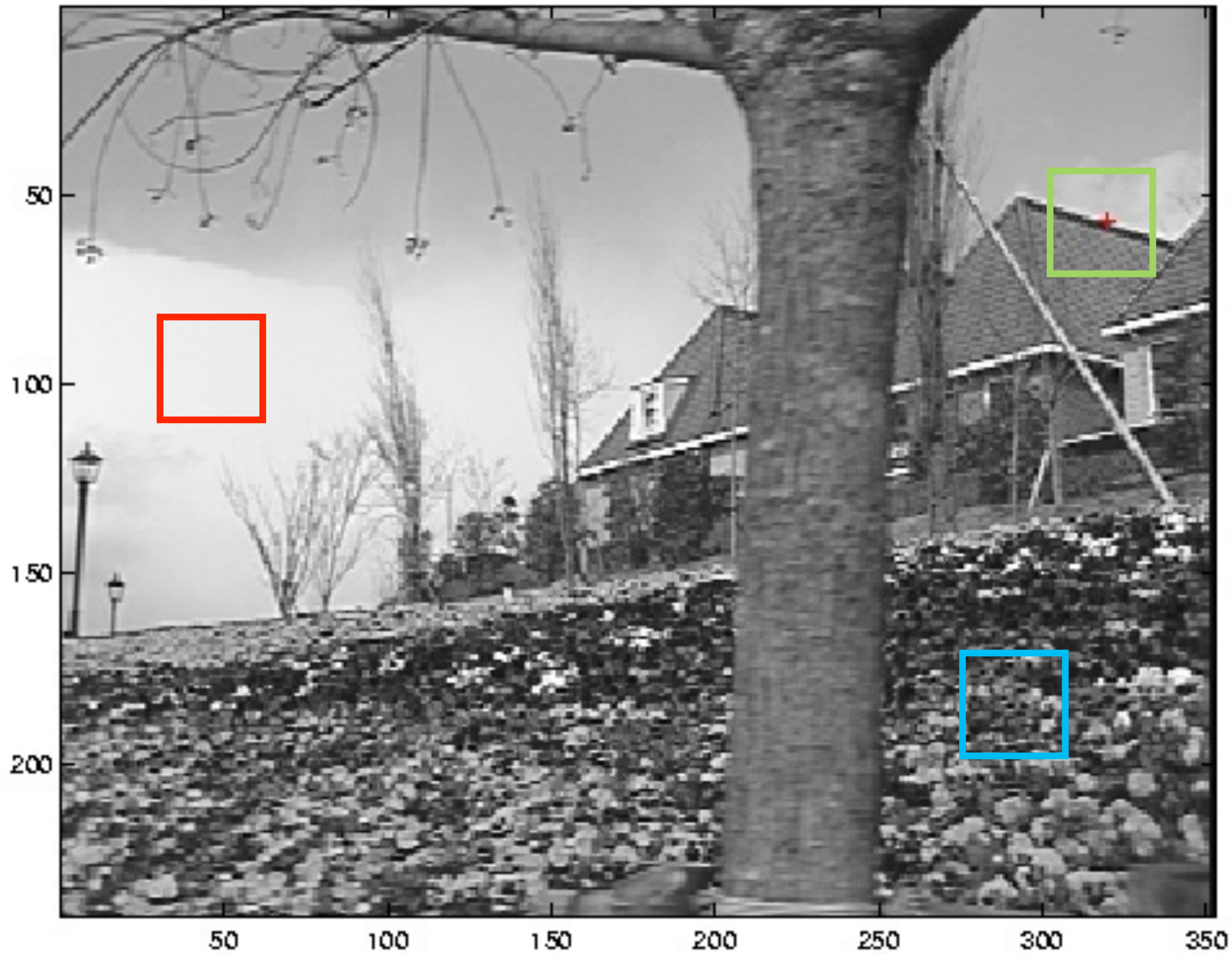
- (u,v) can only be found, if this is solvable, i.e. 2x2 image structure matrix is invertible == with no small eigenvalue
- This matrix and the requirement sound familiar – have we seen these before?
- Recall Harris corner detector!
- Thus, "good image features (with large structural eigenvalues) are also good for tracking (with which we can find motion"

Computer Vision

Interpreting the Eigenvalues



Samples: Edge / Low Texture / High Texture



Example

Computer Vision

Outline

Feature

- Region Tracking (and Mean Shift Algorithm)
- Point Tracking (and Aperture Problem)
- Template Tracking

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  - a specific target
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- Misc (preventing drift, context, issues)

Template Tracking

Template Tracking

- Keep a template image to compare with each frame
- This is typically applied for small patches, e.g. 5x5
- Why not run it for the entire object (for a larger window)

- Locally, translation is sufficient to explain motion; but…

Lucas-Kanade Template Tracker

- Motion is more complex in a larger window

- Nonetheless, we can easily generalize the motion model to other parametric models!

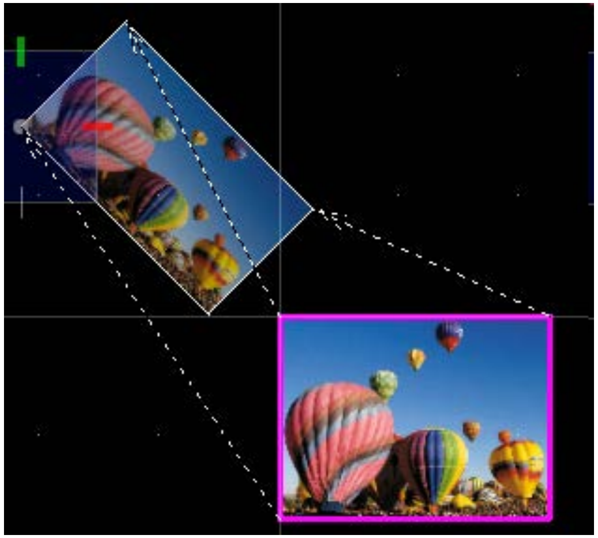
e.g., translation, affine, projective, "warp"

$$E(u,v) = \sum_{x,y} \left[I(x+u, y+v) - T(x,y) \right]^2$$

$$E(p) = \sum_{x,y} \left[I(W(x;p)) - T(x,y) \right]^2$$

Lucas-Kanade Template Tracker

- From Points to templates
- Estimate "optimal" warp W

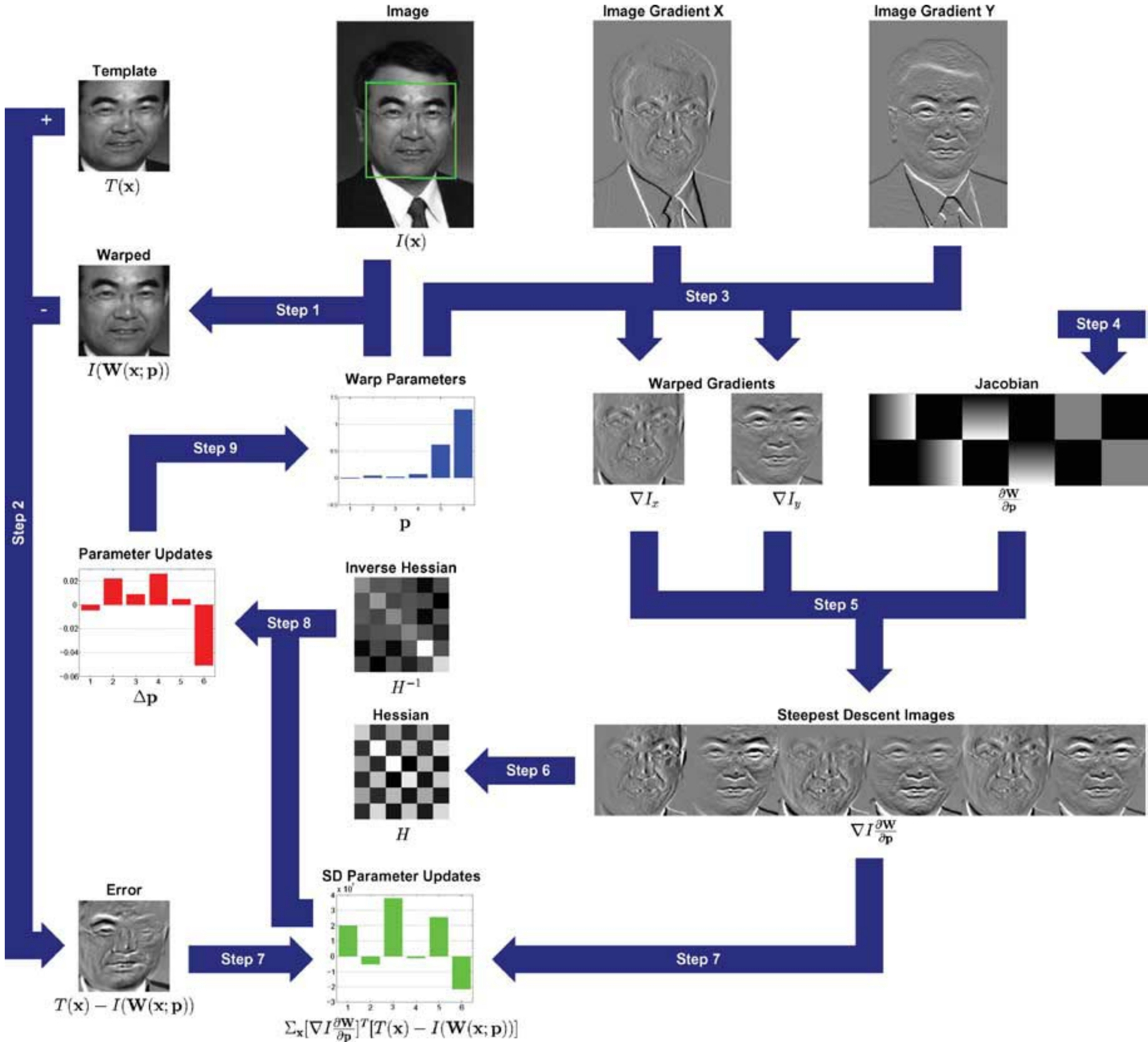


$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x};\mathbf{p})) - T(\mathbf{x})]^2$$

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x};\mathbf{p}+\Delta\mathbf{p})) - T(\mathbf{x})]^2$$

Computer Vision

[Baker & Matthews, IJCV'04, Lucas-Kanade 20 Years On: A Unifying Framework]



Lucas-Kanade Template Tracker

Step 1. Warp I to obtain $I(W([x\ y];P))$

Step 2. Compute the error image $T(x) - I(W([x\ y]; P))$

Step 3. Warp the gradient ∇I with $W([x\ y]; P)$

Step 4. Evaluate $\frac{\partial W}{\partial P}$ at $([x\ y]; P)$ (Jacobian)

Step 5. Compute steepest descent images $\nabla I \frac{\partial W}{\partial P}$

Step 6. Compute Hessian matrix $\sum (\nabla I \frac{\partial W}{\partial P})^T (\nabla I \frac{\partial W}{\partial P})$

Step 7. Compute $\sum (\nabla I \frac{\partial W}{\partial P})^T (T(x,y) - I(W([x,y];P)))$

Step 8. Compute ΔP

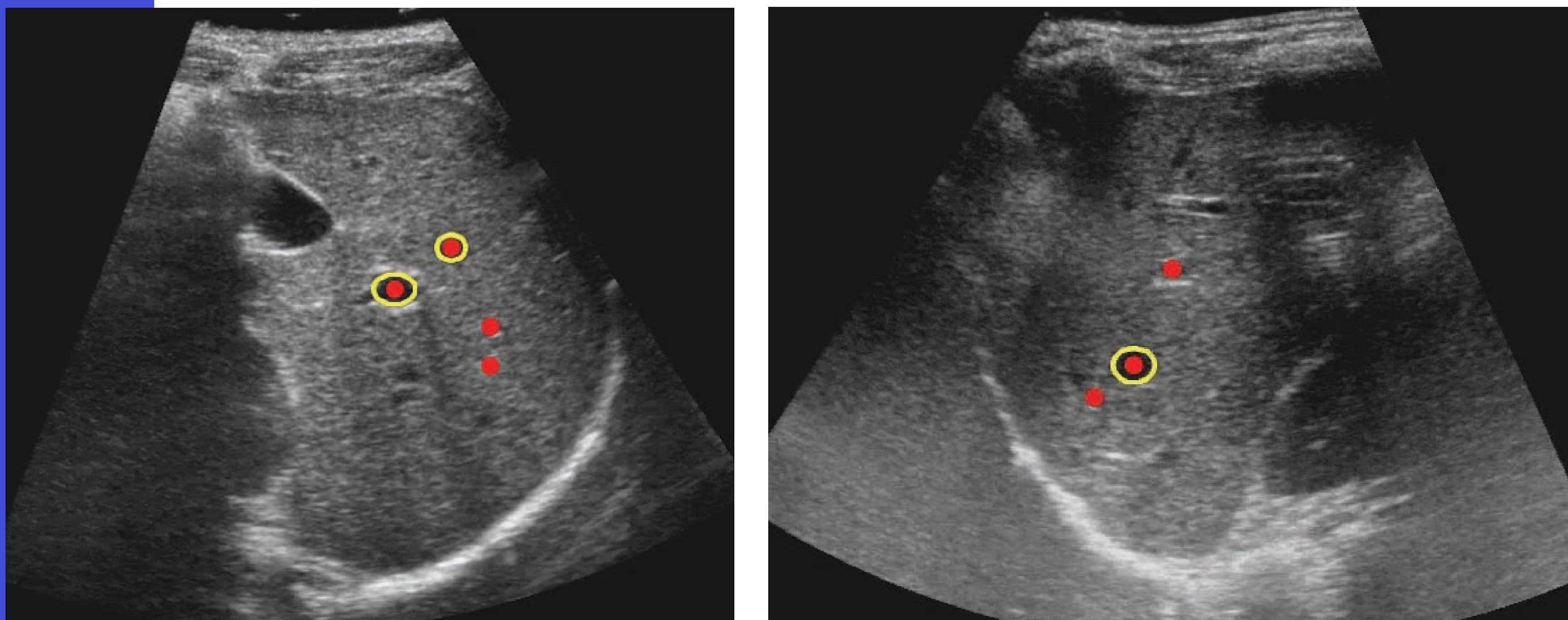
Step 9. Update $P \longleftarrow P + \Delta P$

Example

Computer Vision

Example: Tracking Liver in Ultrasound

[Makhinya and Goksel: **"Motion Tracking in 2D Ultrasound Using Vessel Models and Robust Optic-Flow"**, MICCAI CLUST, 2015]



● Our tracking
+ Manual annotation

Computer Vision

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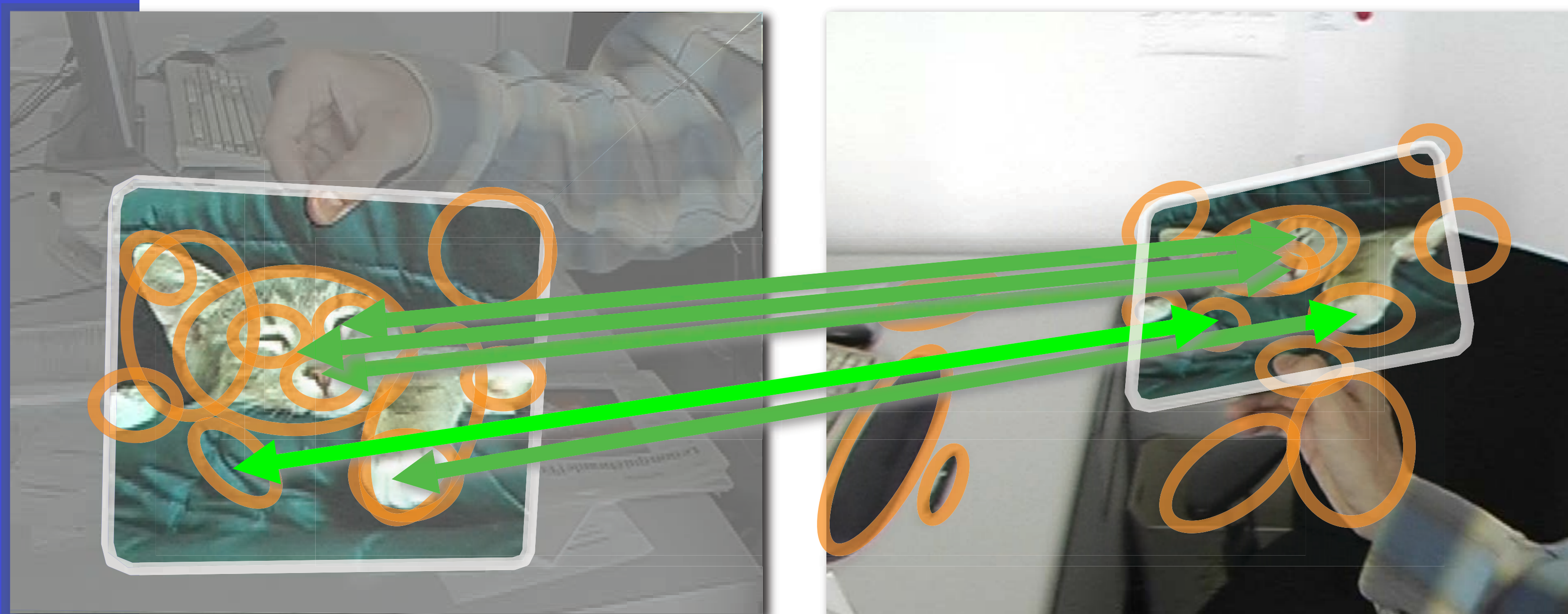
Tracking by Detection

(of a specific target)

3D Object Detection



Reference image(s) of the object to detect

Test image

3D Object Detection

MathWorks

Reference image(s) of the object to detect

Test image

Computer Vision

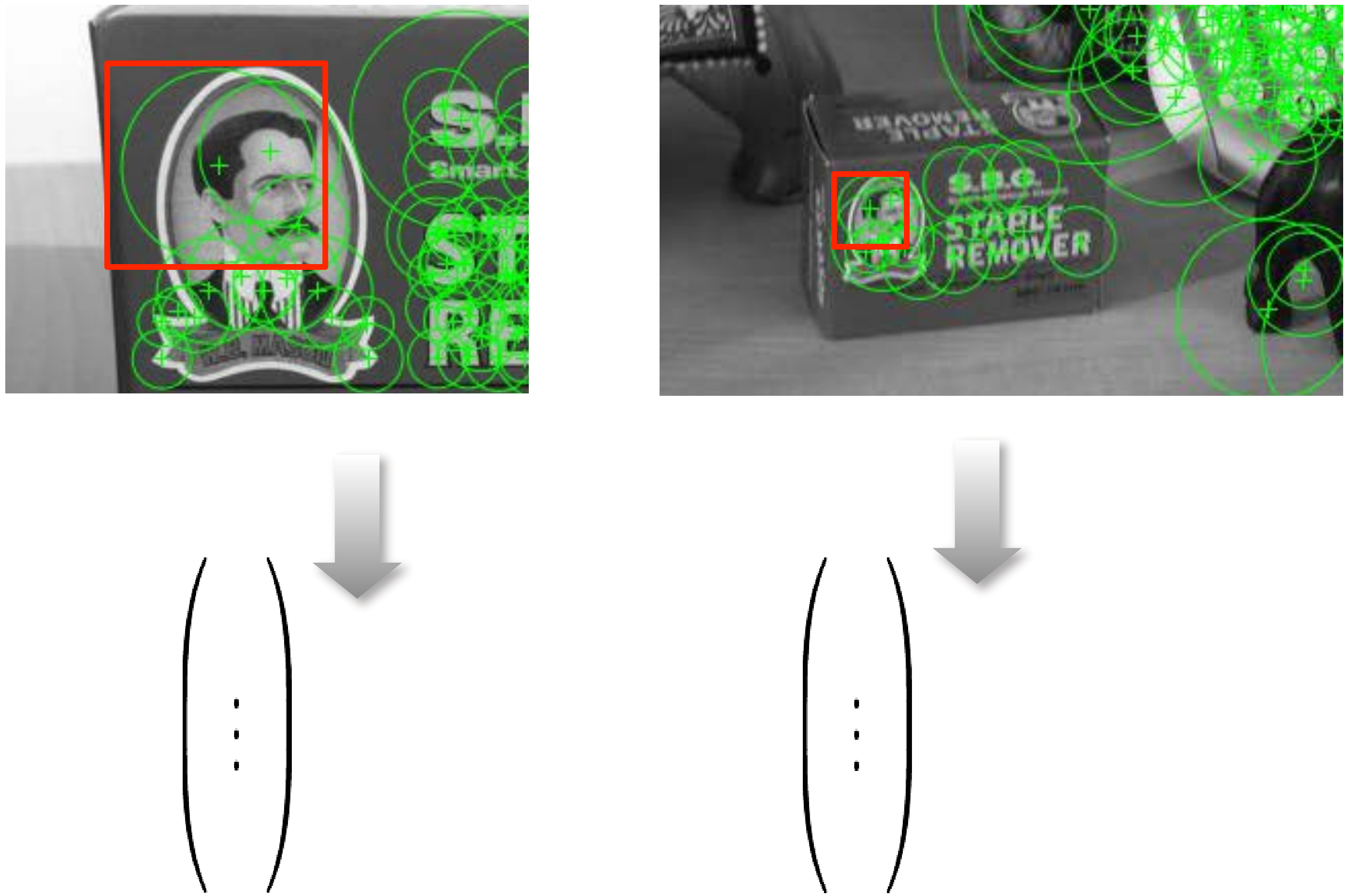
1. Detect Keypoints

– invariant to scale, rotation, or perspective

100 strongest feature points in the reference image

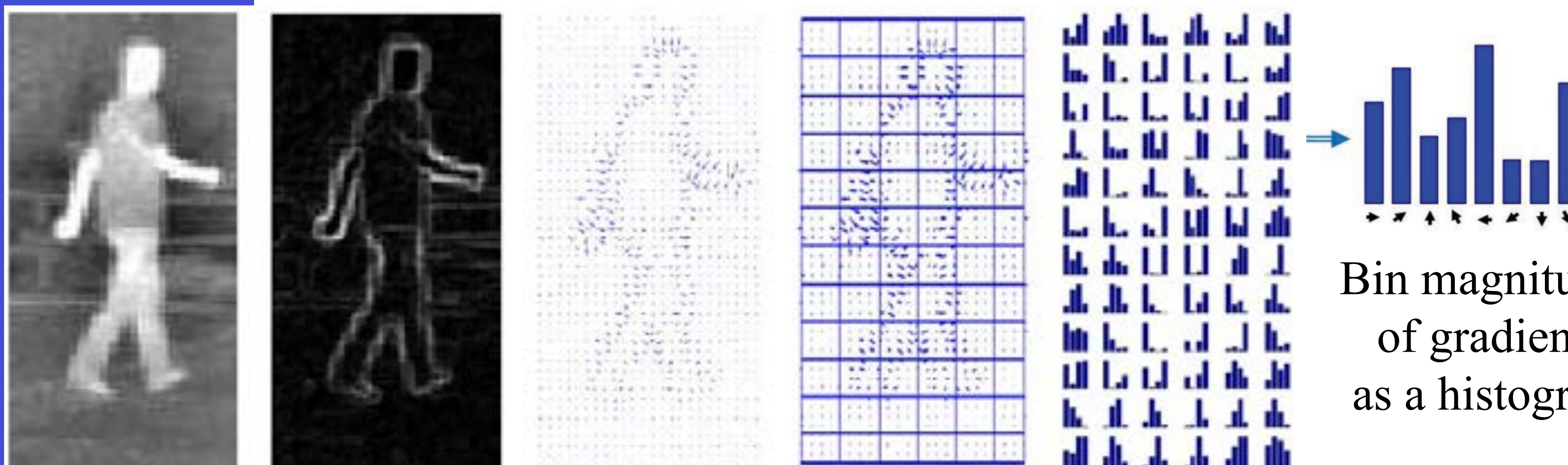
300 strongest feature points in the test image

2. Build Feature Descriptors



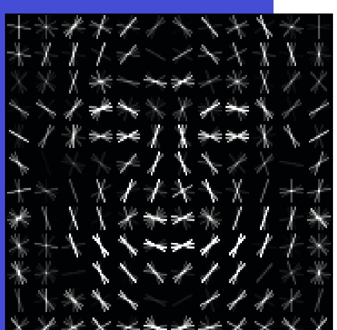
Histogram of Oriented Gradients

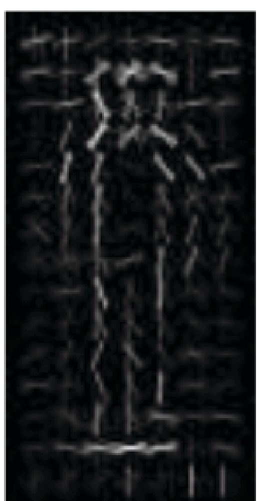
Example: HOG is a (rotation invariant) feature descriptor

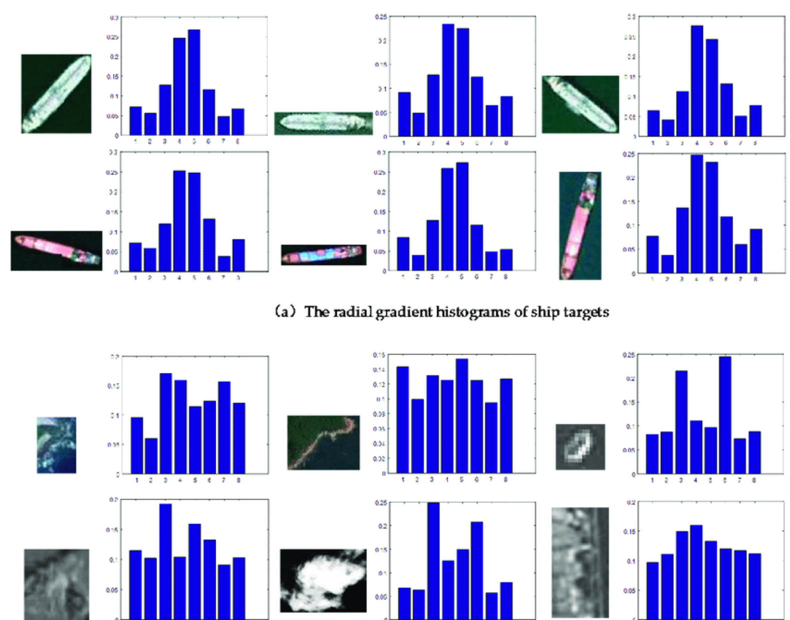


Bin magnitudes of gradients as a histogram

Useful to track specific points





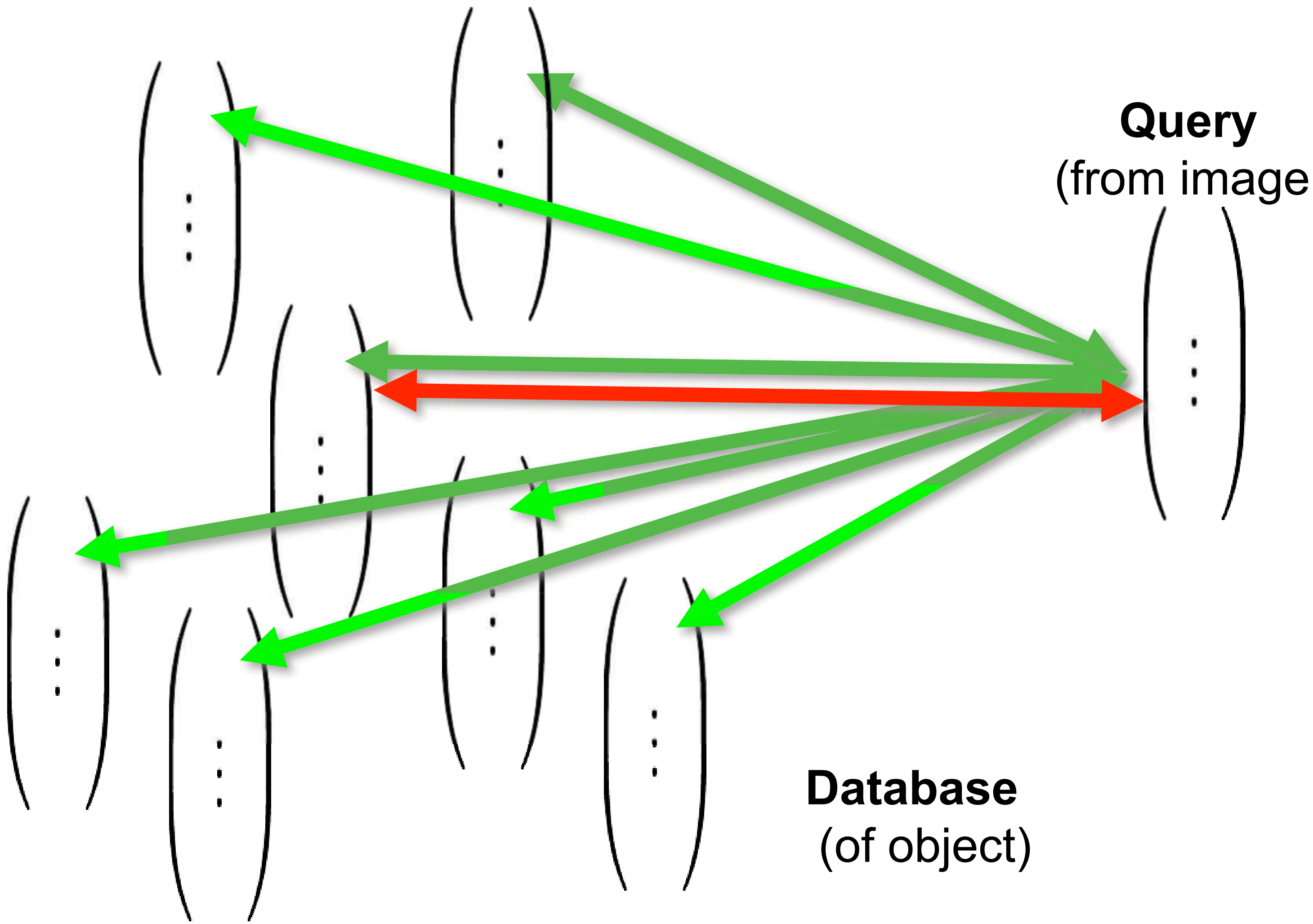


Also, object shapes defined by edges, thus HOG over entire objects can be descriptive

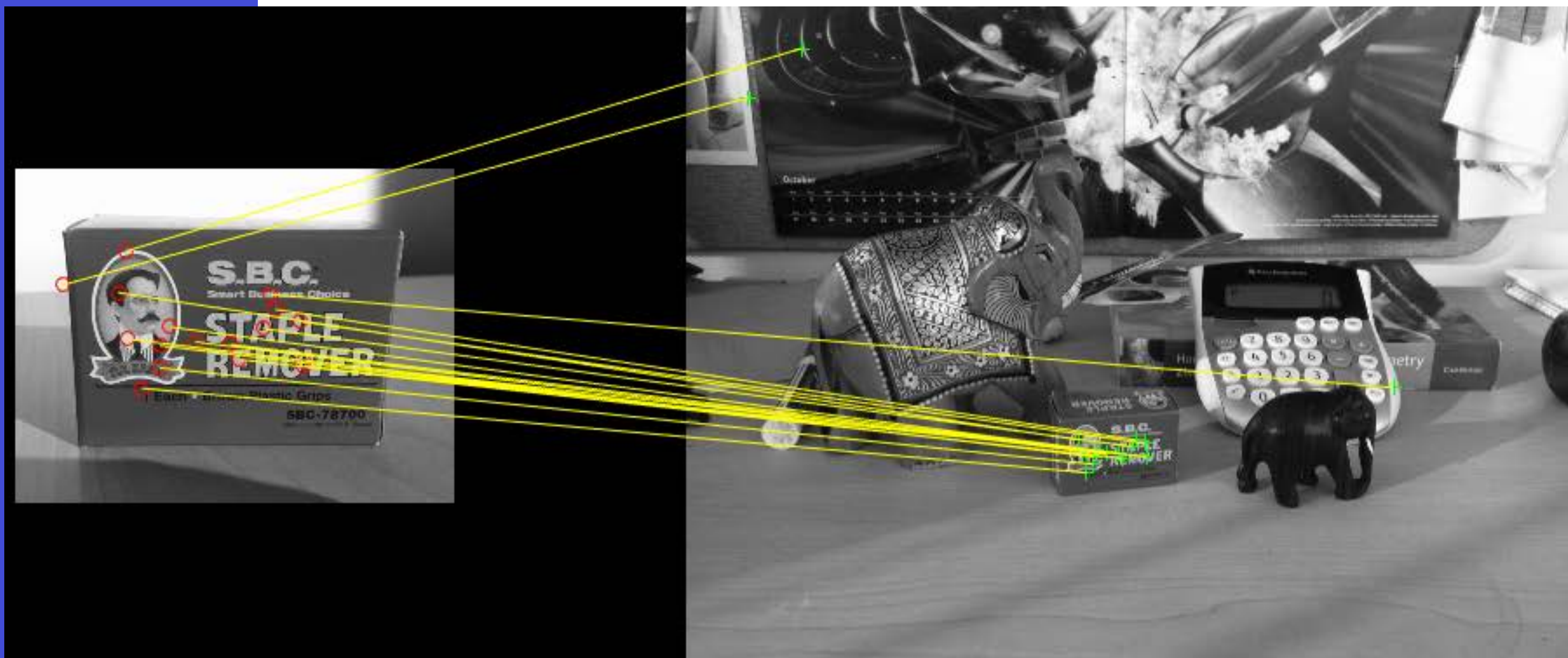
See also **SIFT, SURF, ...**

3. Match Keypoint Descriptors

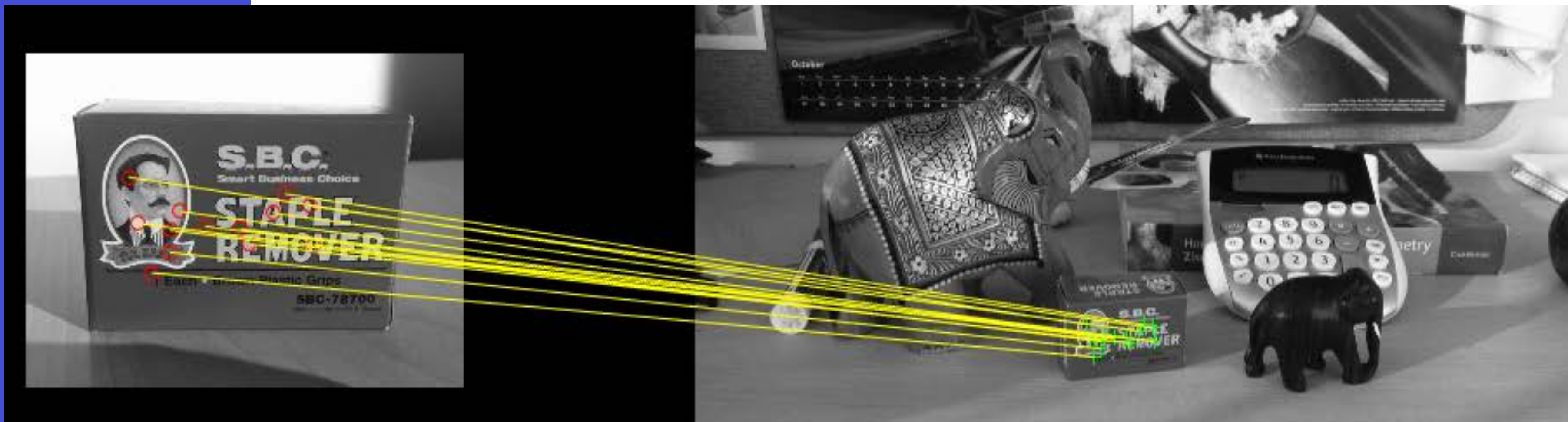
- Search in the Database



3. Search in the Database



4. Outlier Elimination



Summary

Keypoint Detection

Keypoint Recognition

Search in the Database

Robust 3D Pose Calculation

(RANSAC)

Geometric verification

Computer Vision

[Wagner et al. ISMAR'08]

Computer Vision

[Wagner et al. '09]

Computer Vision

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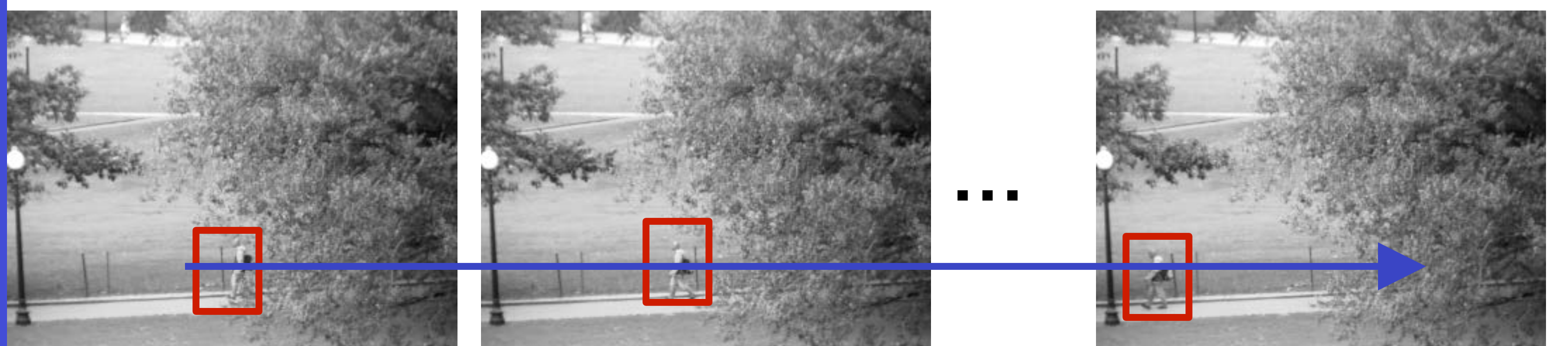
Tracking by Detection

(of the object class)

also for “Multiple Object Tracking”

Tracking-by-Detection

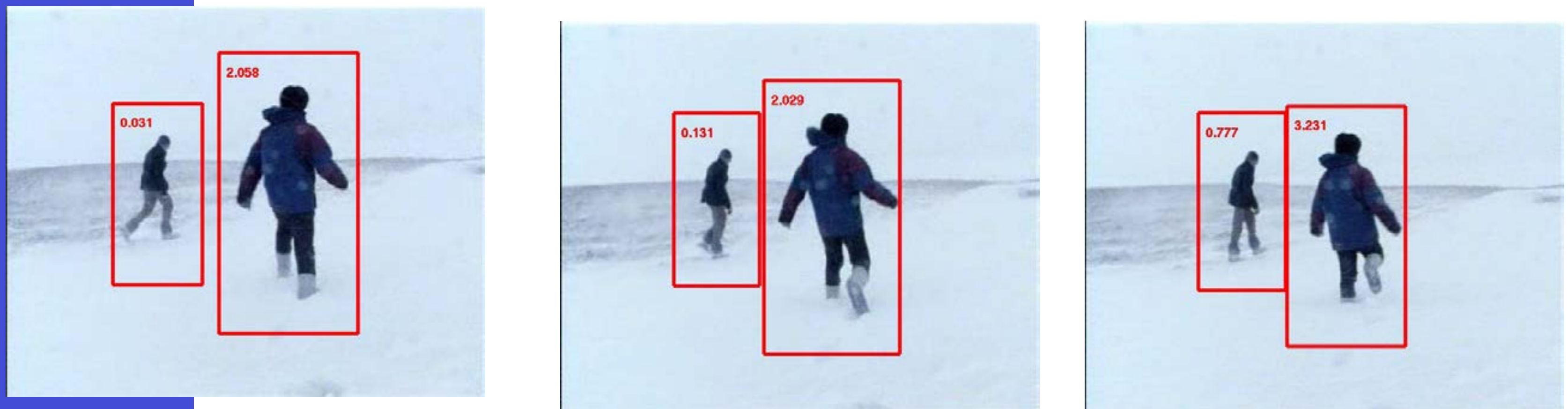


detect object(s) independently in each frame

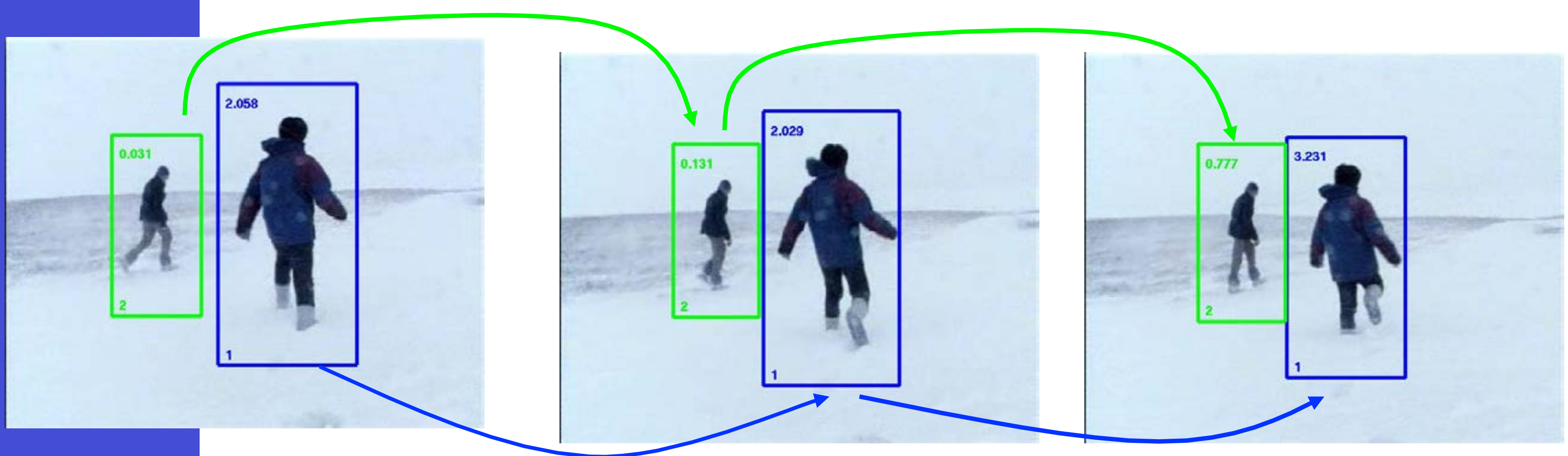
associate detections over time into *tracks*

Computer Vision

Multiple Objects



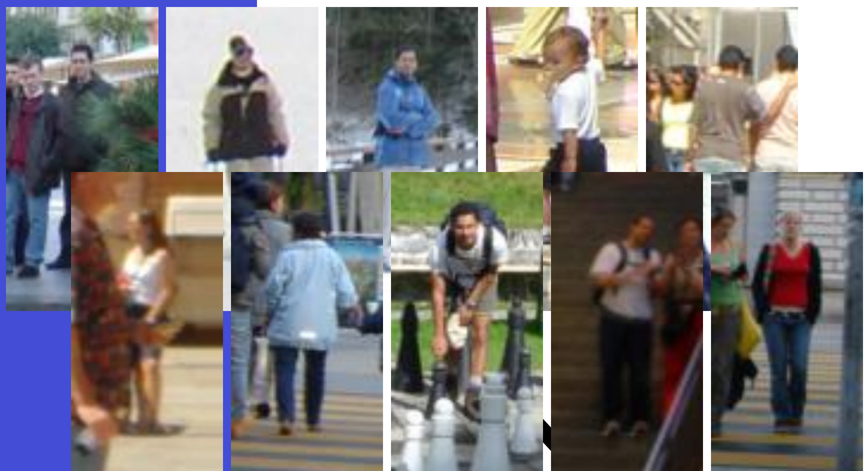
Frame 1 Frame 5 Frame 9



Computer Vision

Examples: Multiple Object Tracking

How to get the detections?



Persons

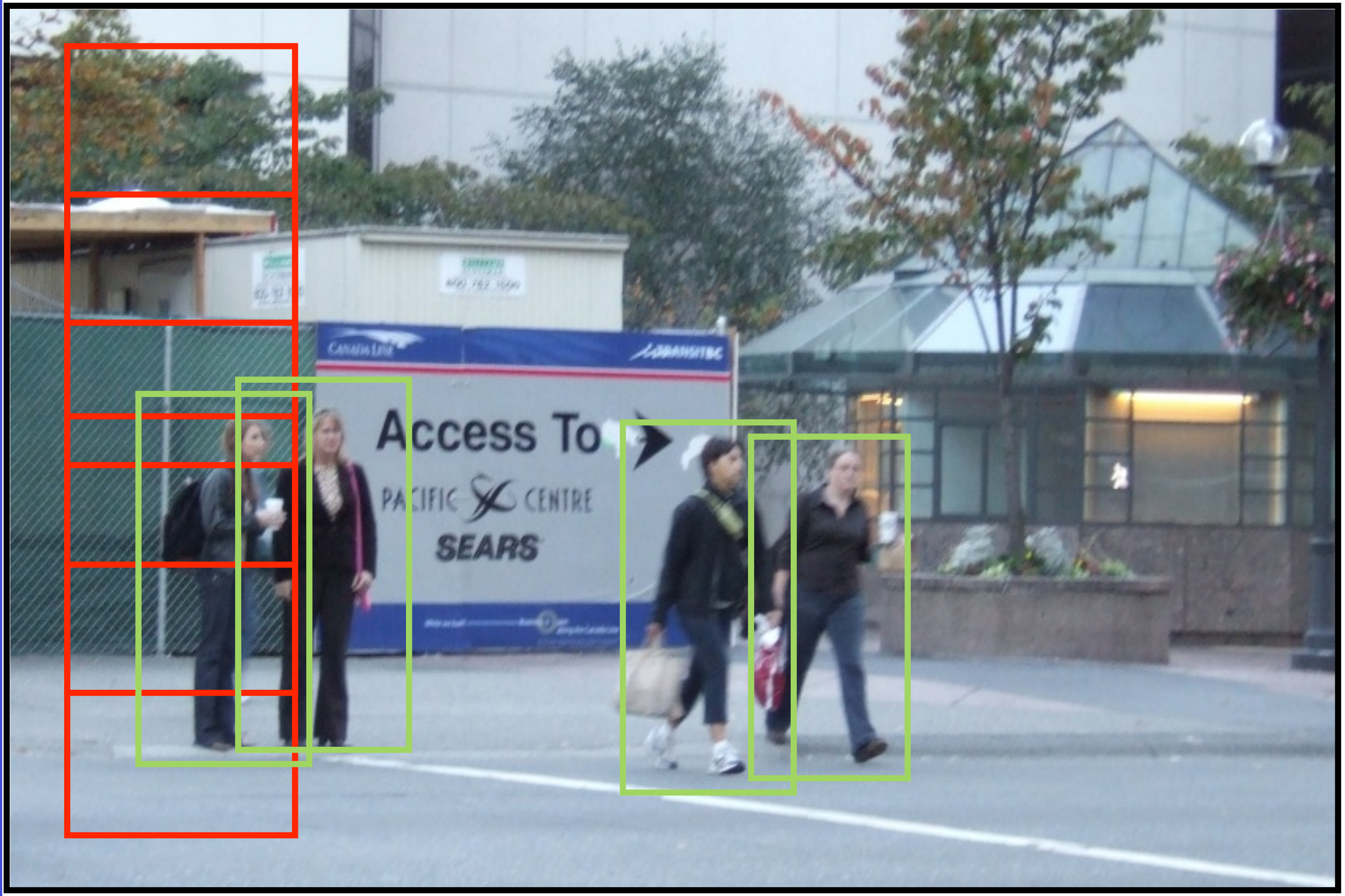
Background

Supervised Learning

(Support Vector Machines,
Random Forests,
Neural Networks, ...)

Computer Vision

Using the classifier



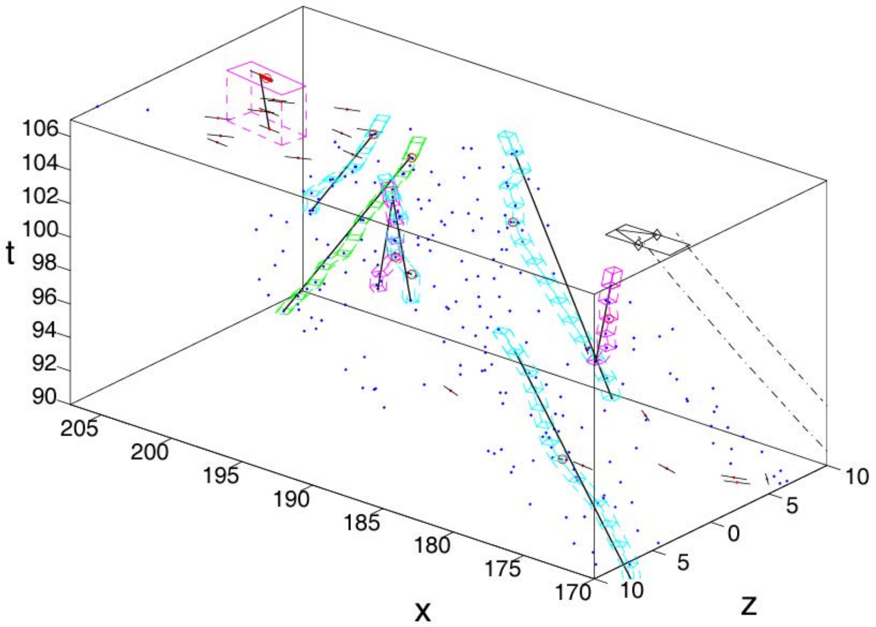
Computer Vision

Space-Time Analysis

- Collect detections in space-time volume

Detections

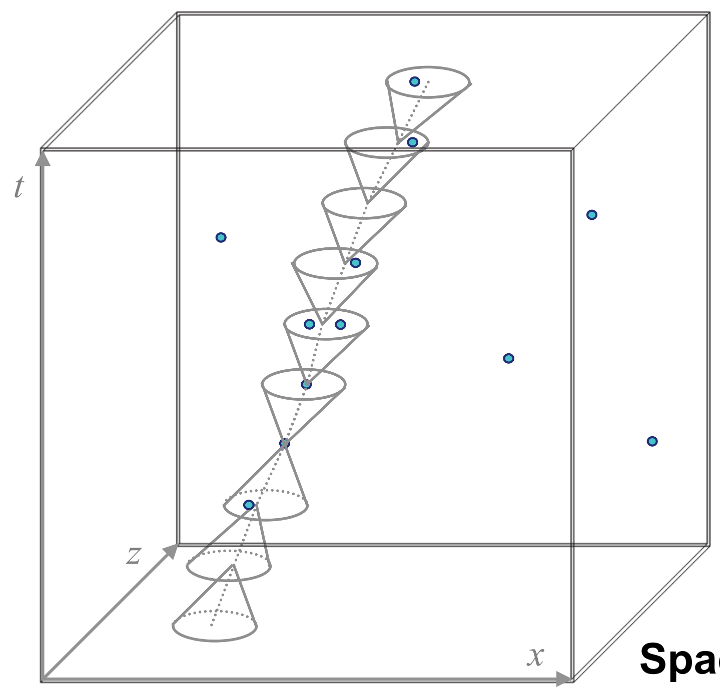
Space Time Volume



[Leibe et al. CVPR'07]

Trajectory Estimation

- Trajectory growing and selection

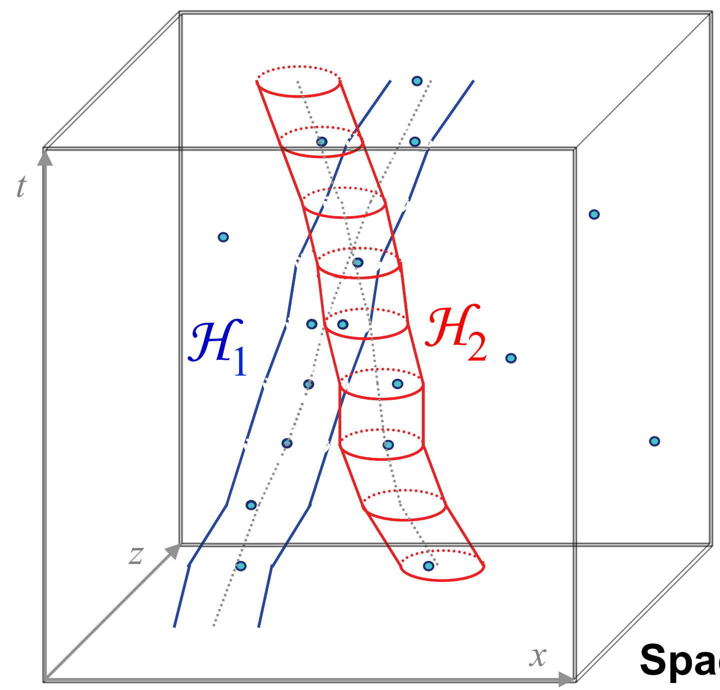


Space Time Volume

Computer Vision

Trajectory Estimation

- Trajectory growing and selection



Space Time Volume

Computer Vision

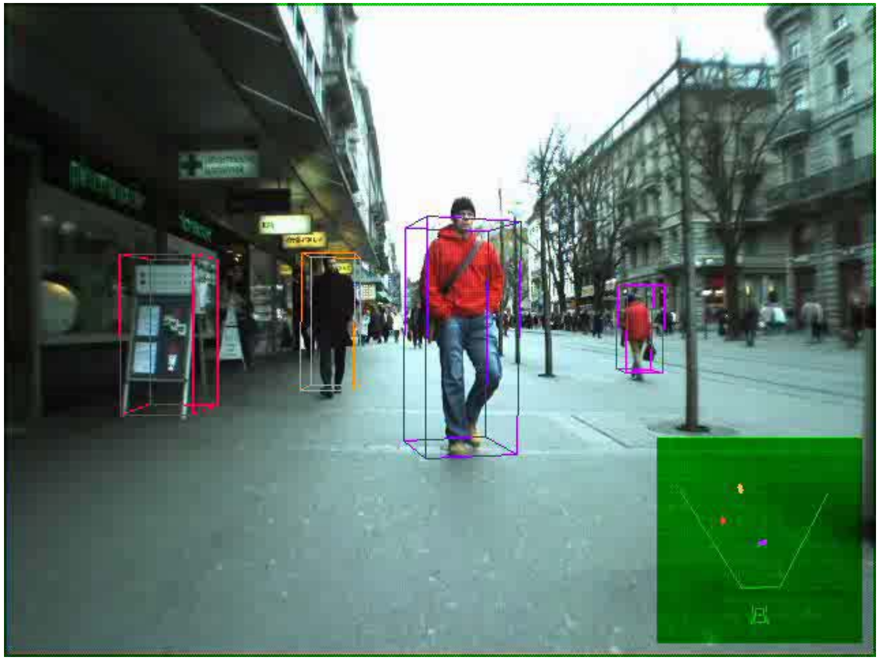
Driving

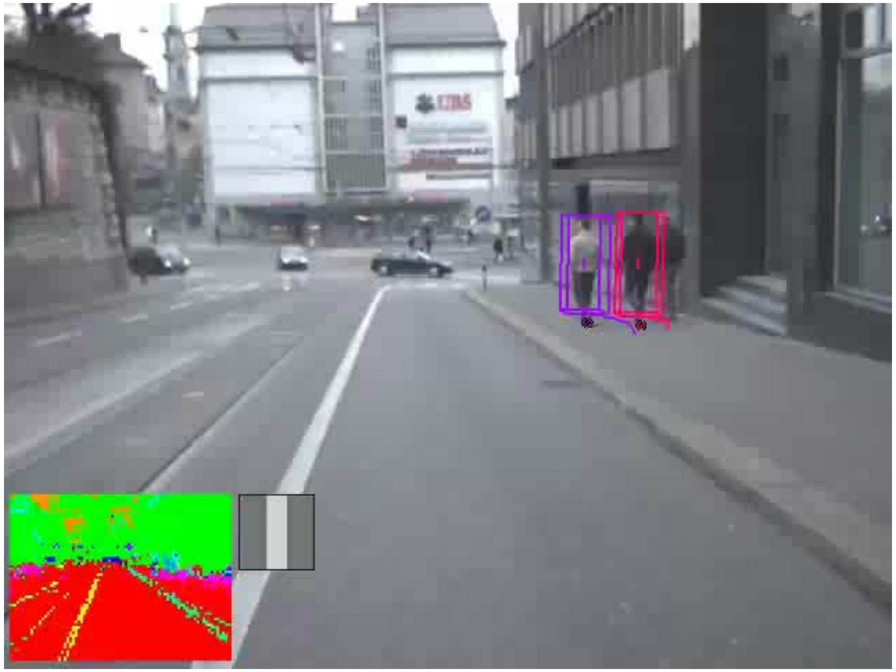
Input (Object Detections)

“Tracking” Result

Computer Vision

[Ess et al. CVPR'08]





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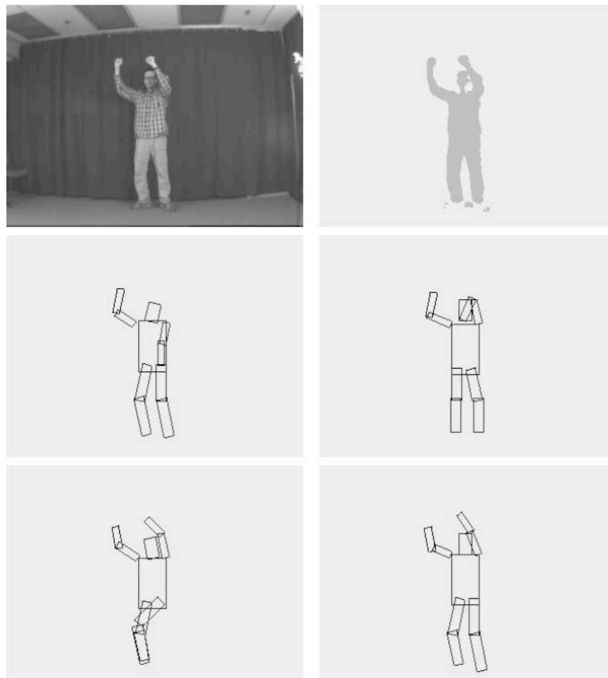
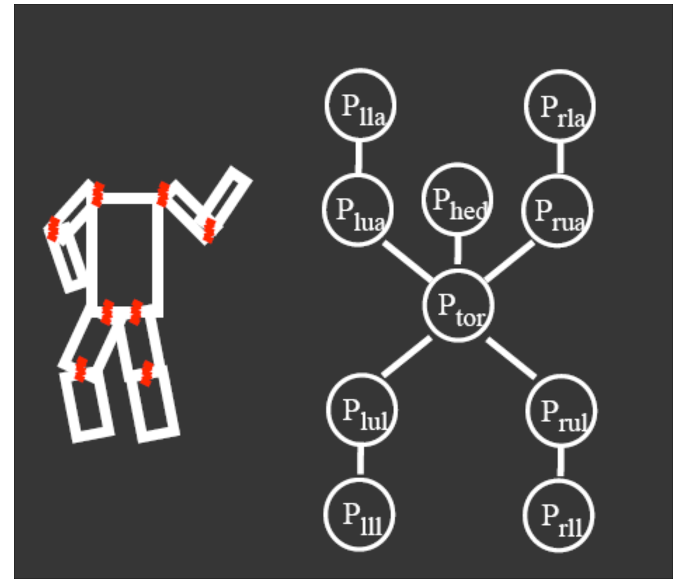
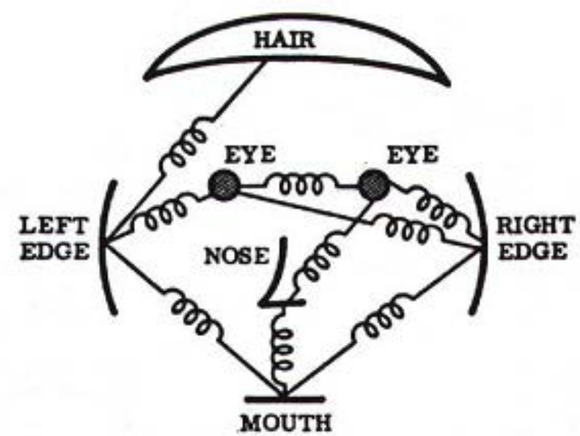
Model based Tracking

Articulated Tracking: Part-Based Models



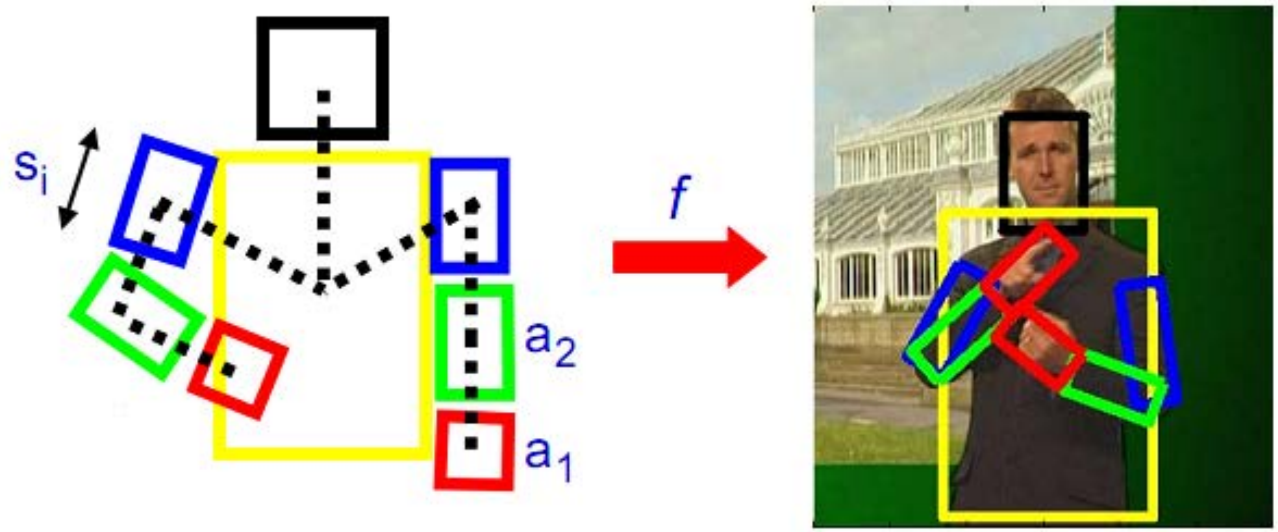


- Intuitive model of an object
- Model has two components
  1. parts (2D image fragments)
  2. structure (configuration of parts)
- Dates back to Fischler & Elschlager 1973



Parts-based analysis

Objective: detect human and determine upper body pose (layout)

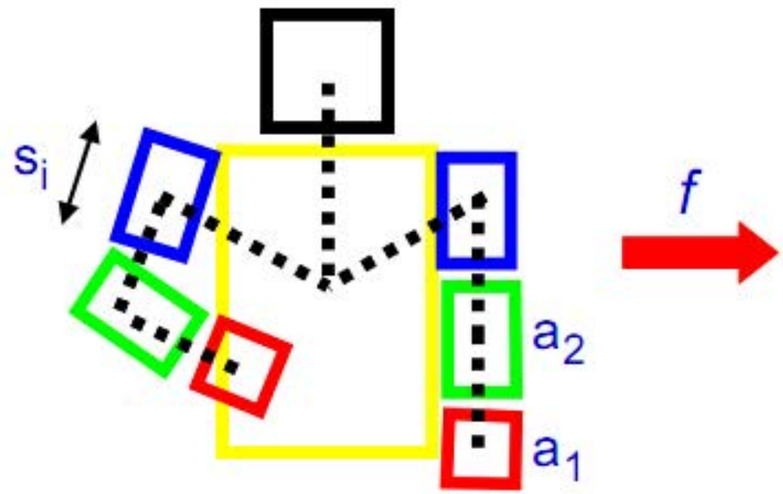


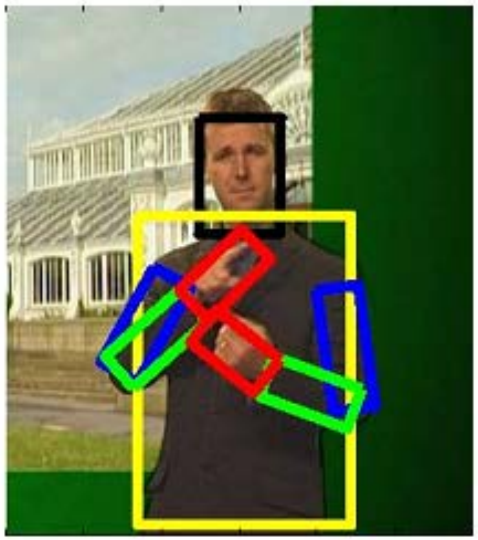
Model as a graph labelling problem

- Vertices $\mathcal{V}$ are parts, $a_i, i = 1, \cdots, n$
- Edges $\mathcal{E}$ are pairwise linkages between parts
- For each part there are h possible poses $\mathbf{p}_j = (x_j, y_j, \phi_j, s_j)$
- Label each part by its pose: $f : \mathcal{V} \longrightarrow \{1, \cdots, h\}$, i.e. part a takes pose $\mathbf{p}_{f(a)}$.

Parts-based analysis

Pictorial structure model – CRF





- Each labelling has an energy (cost):

$$E(f) = \underbrace{\sum_{a \in \mathcal{V}} \theta_{a;f(a)}}_{\substack{\text{unary terms} \\ \text{(appearance)}}} + \underbrace{\sum_{(a,b) \in \mathcal{E}} \theta_{ab;f(a)f(b)}}_{\substack{\text{pairwise terms} \\ \text{(configuration)}}}$$

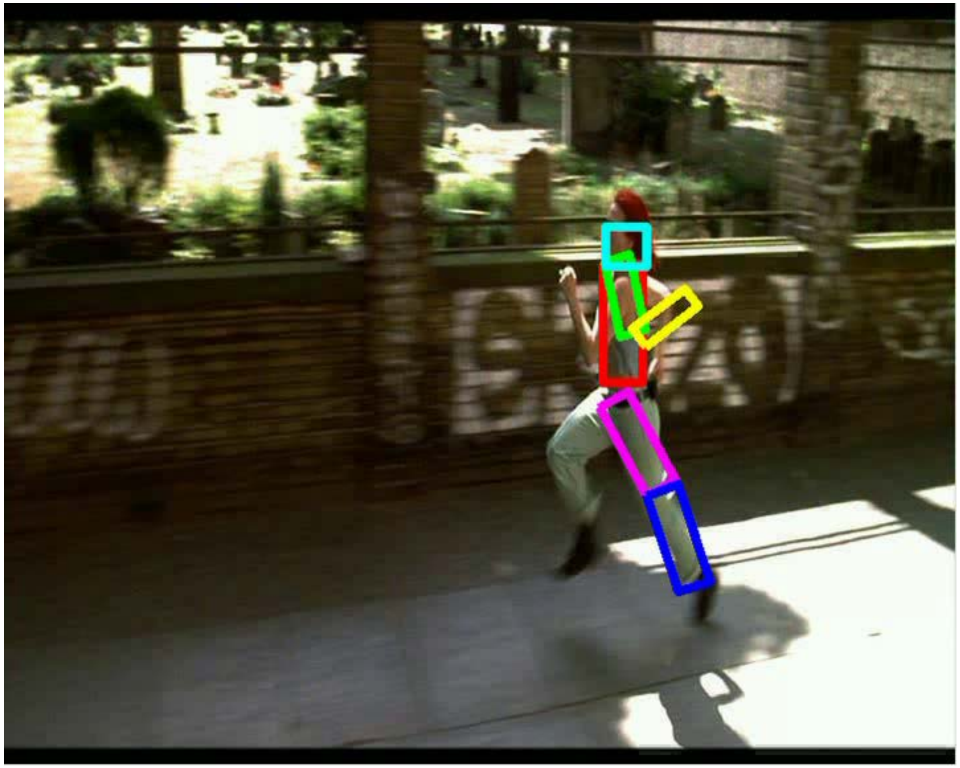
- Fit model (inference) as labelling with lowest energy

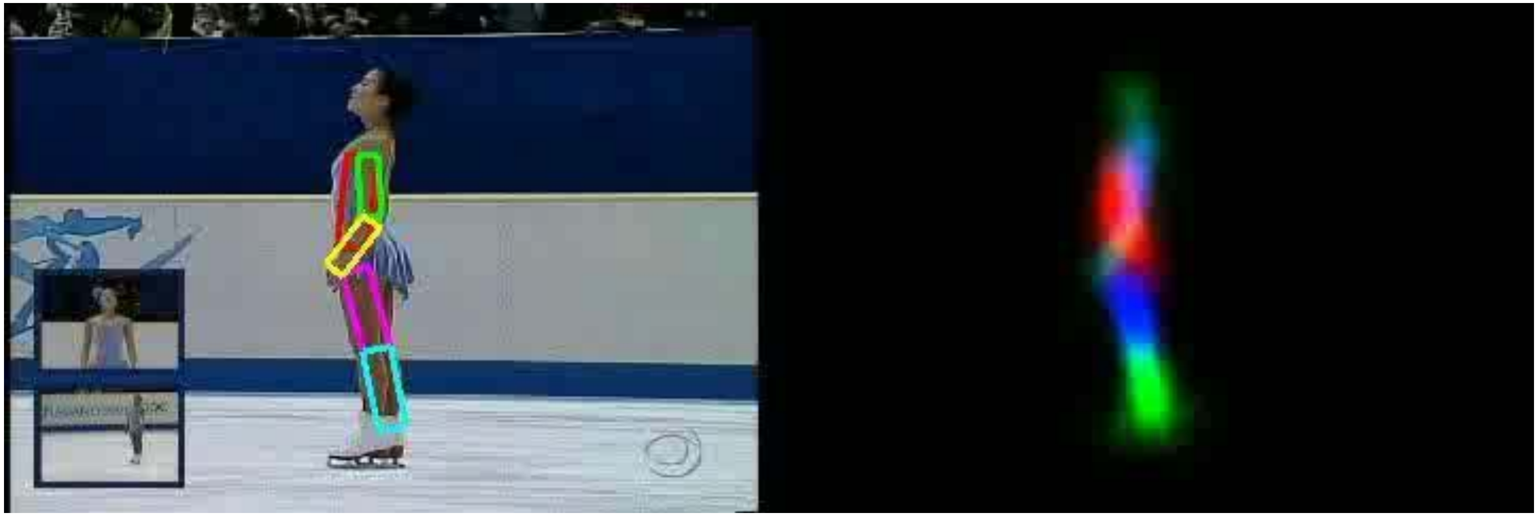
Features for unary:

- colour
- HOG

for limbs/torso

Computer Vision





[Ramanan et al. CVPR'05]

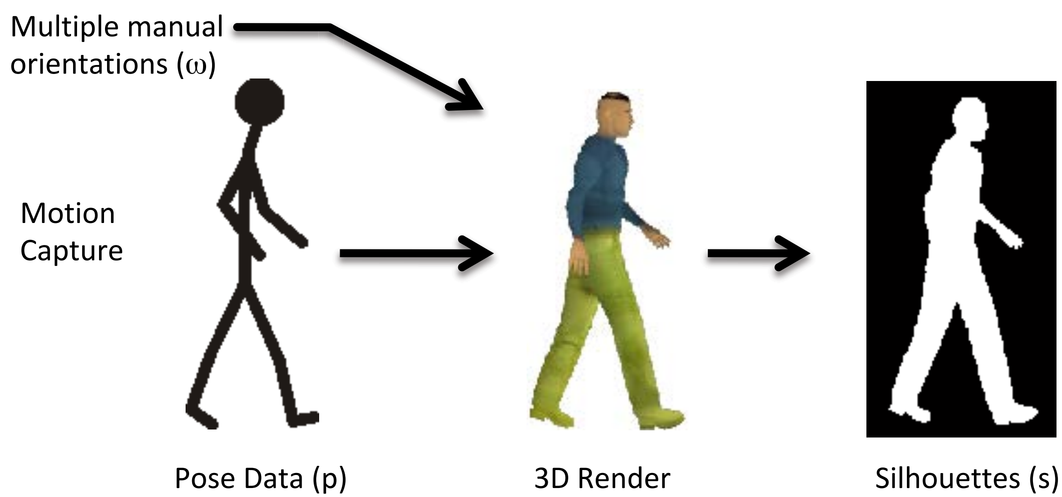
Walking

- What temporal info can we use for tracking?
- What variation would we expect in population?

Articulation Space

Tracking Articulated Motion as High-Dimensional Inference

- Walking cycles have one main (periodic) DOF
- Regressors to learn this (latent) space, and its variation (Gaussian Process regression, **PCA**, etc)
- (Pose,Silhouette) training data can be obtained by 3D rendering



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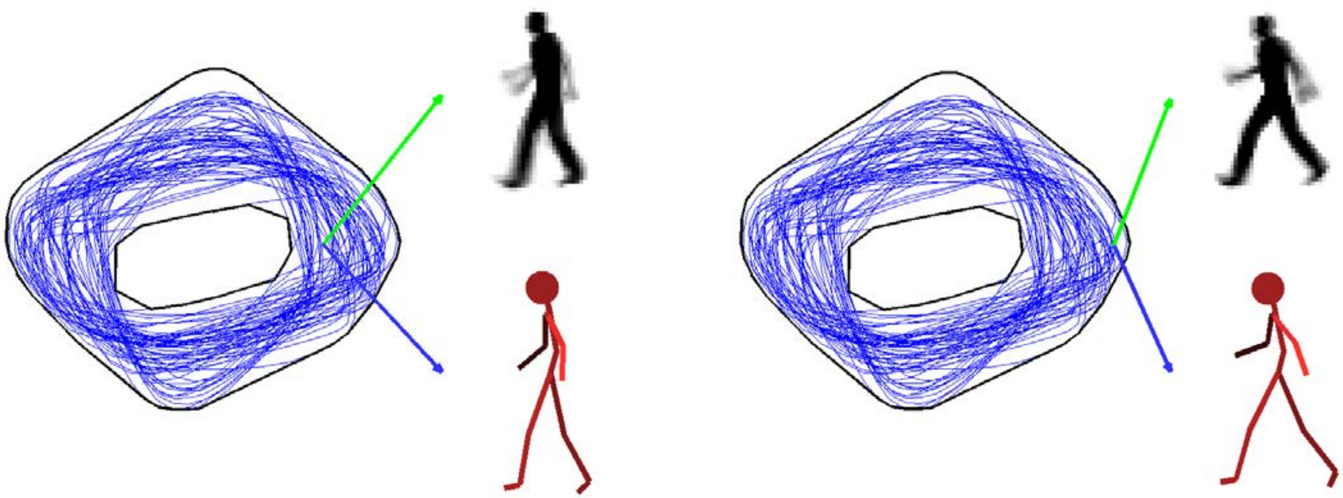

P(Silhouette|k)
perform inference
on silhouettes

P(Pose|k)
recover pose
from latent space

Articulation Space Tracking

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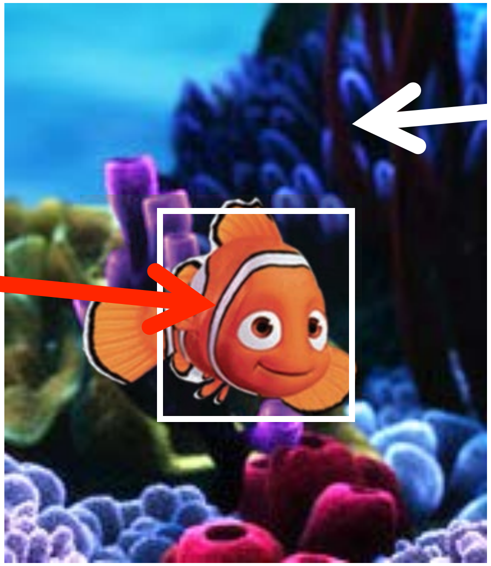
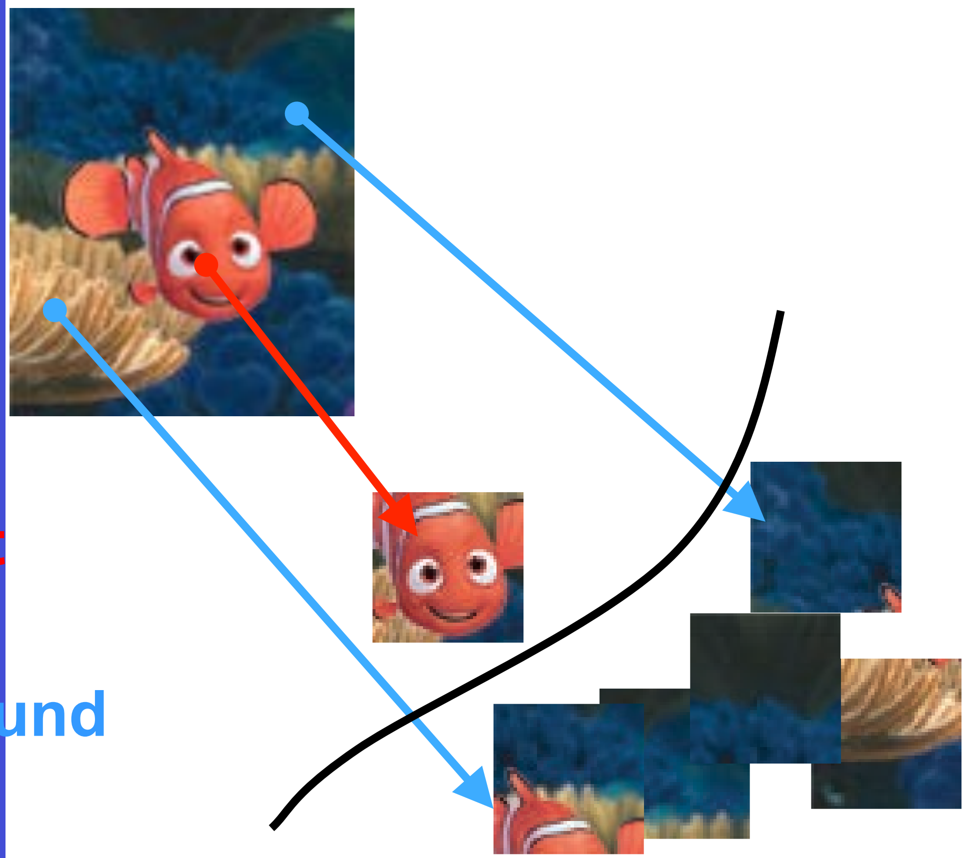
Tracking as On-line learning (updating tracking models)

Tracking as Classification

- Learning current object appearance vs. local background.

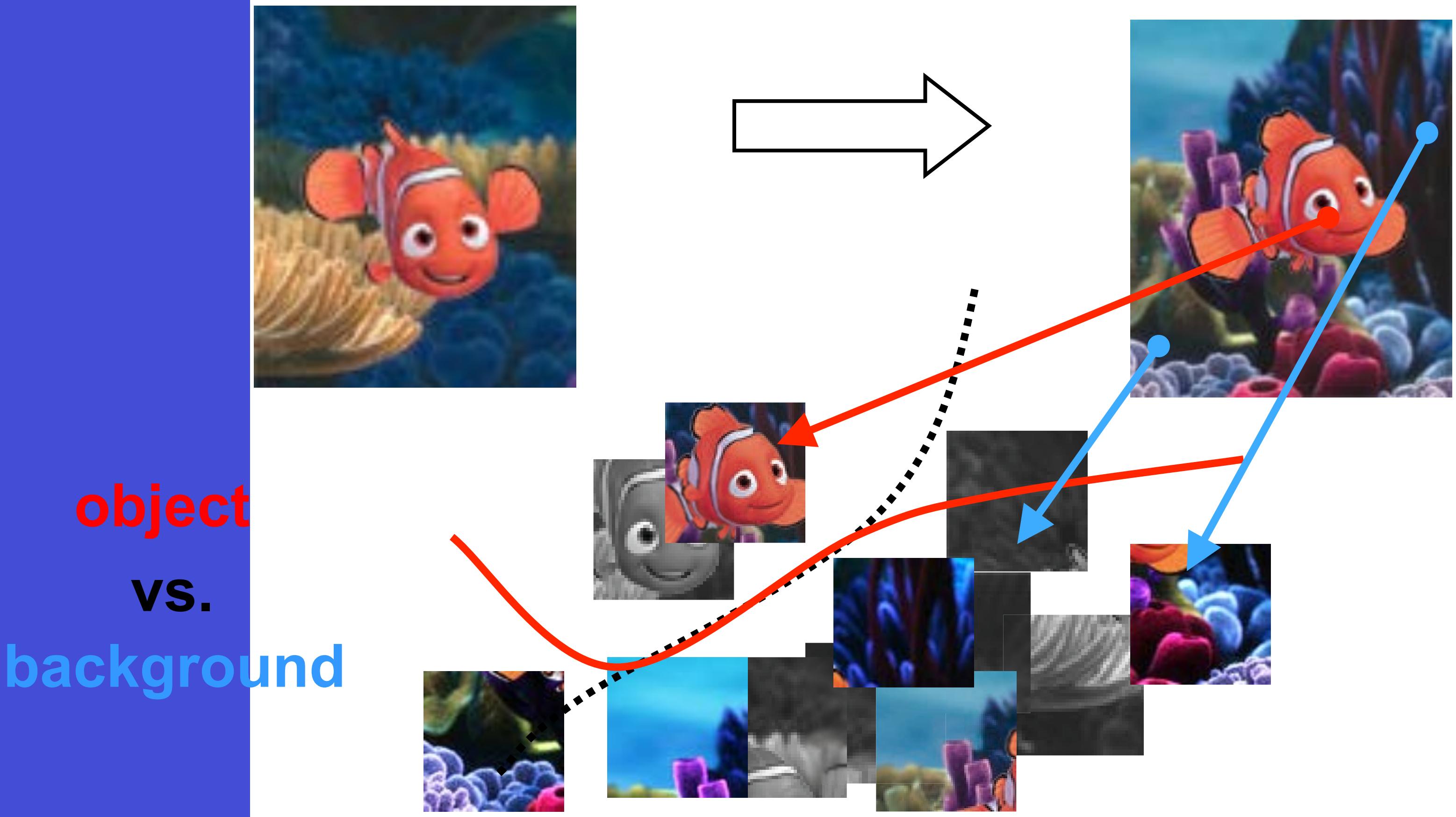


Tracking as Classification

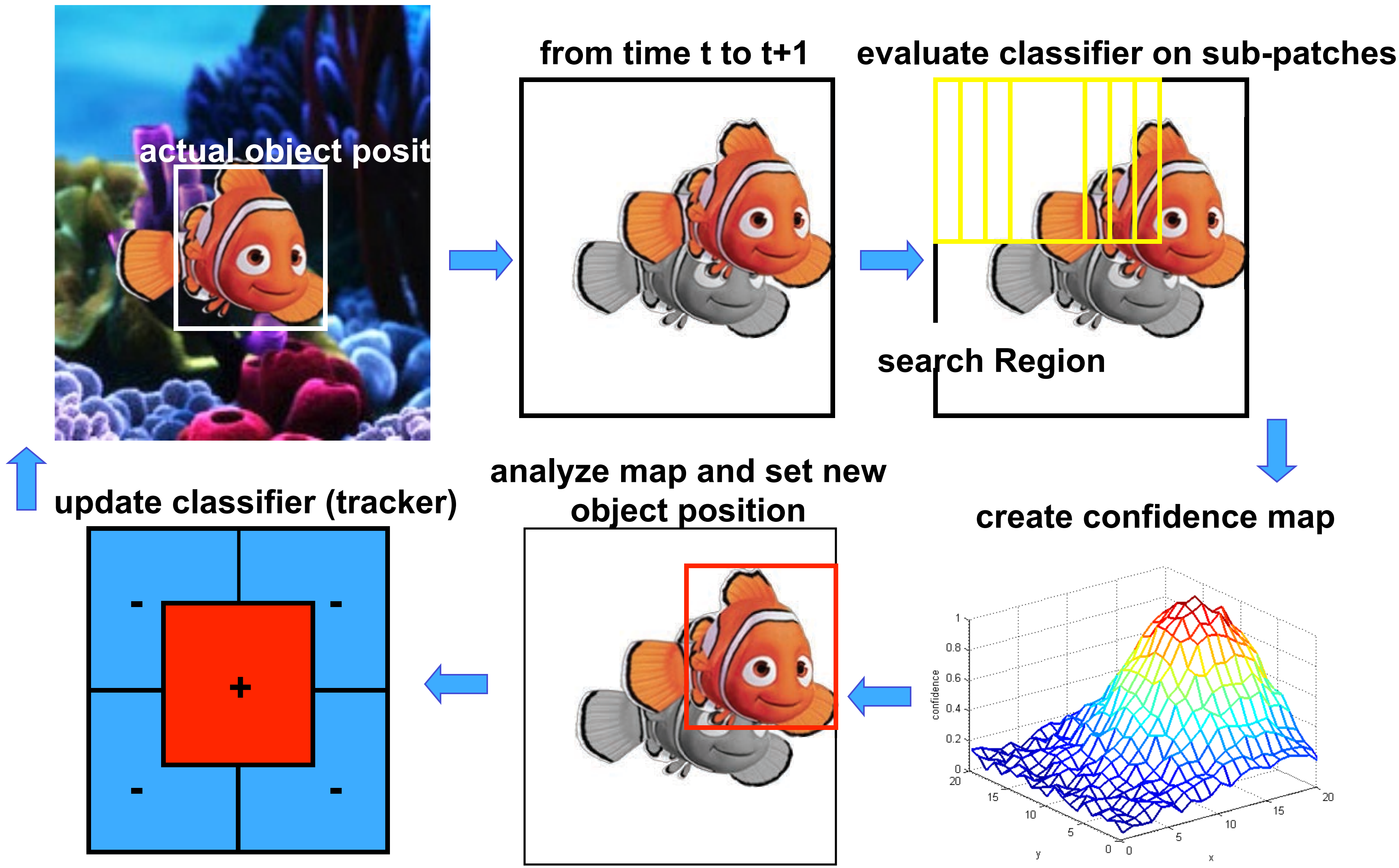


Computer Vision

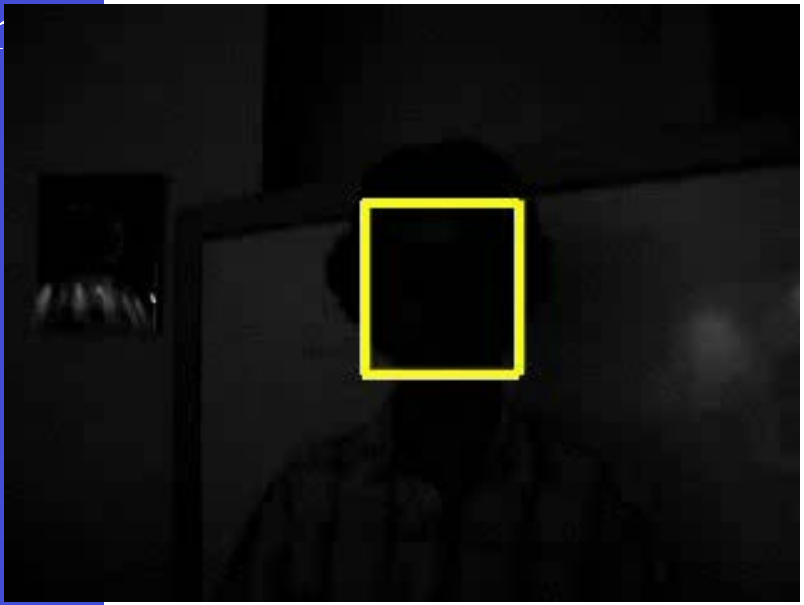
Tracking as Classification

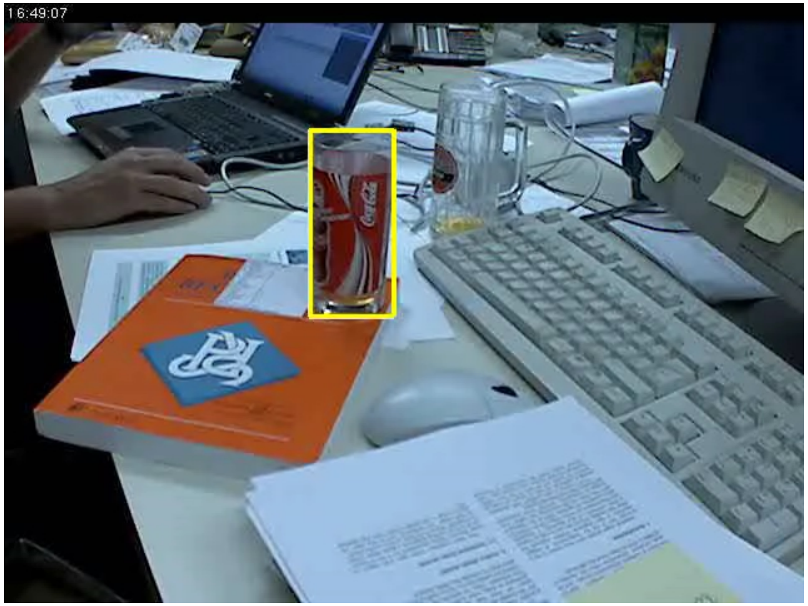


Tracking Loop



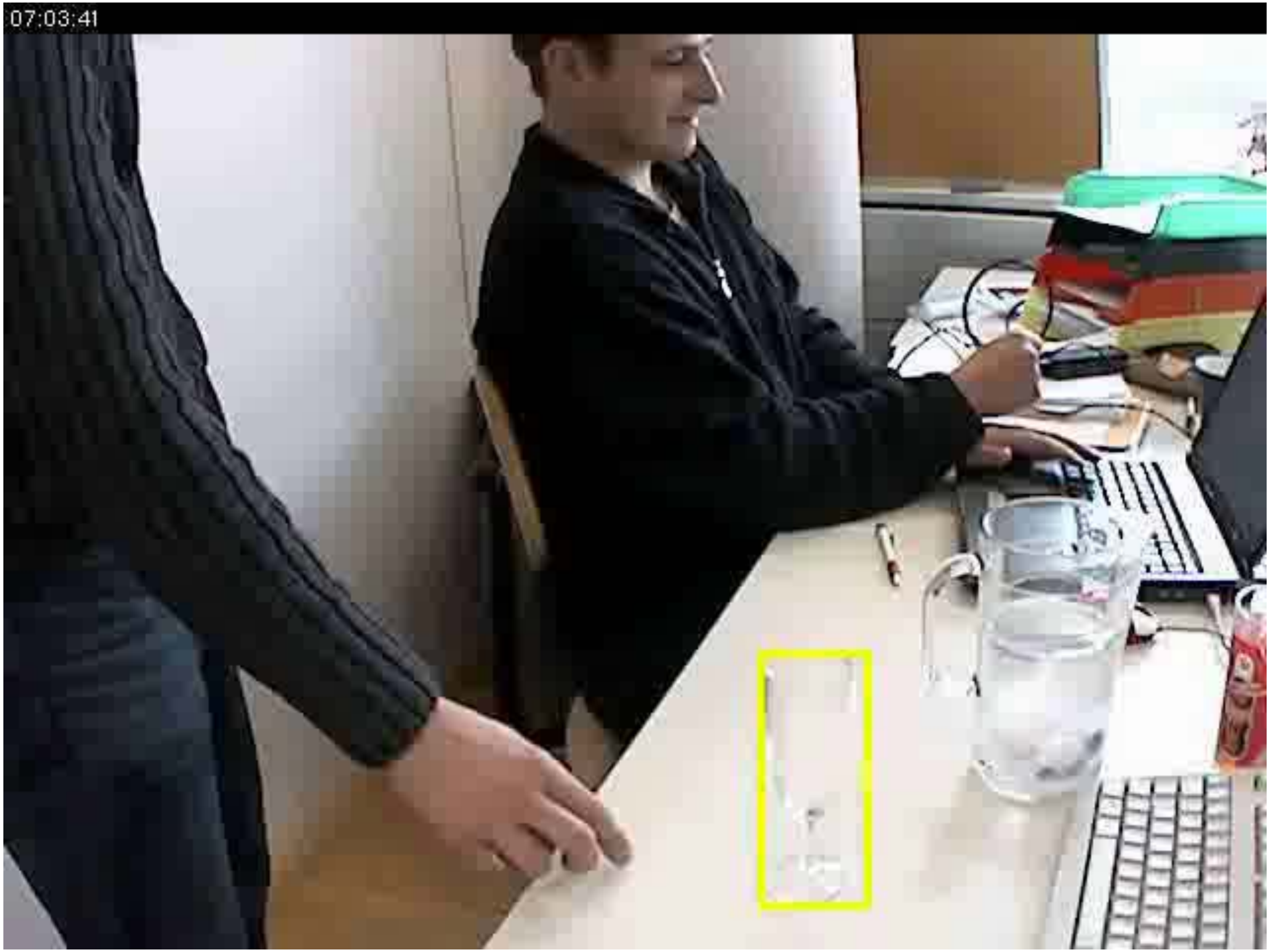
Computer Vision





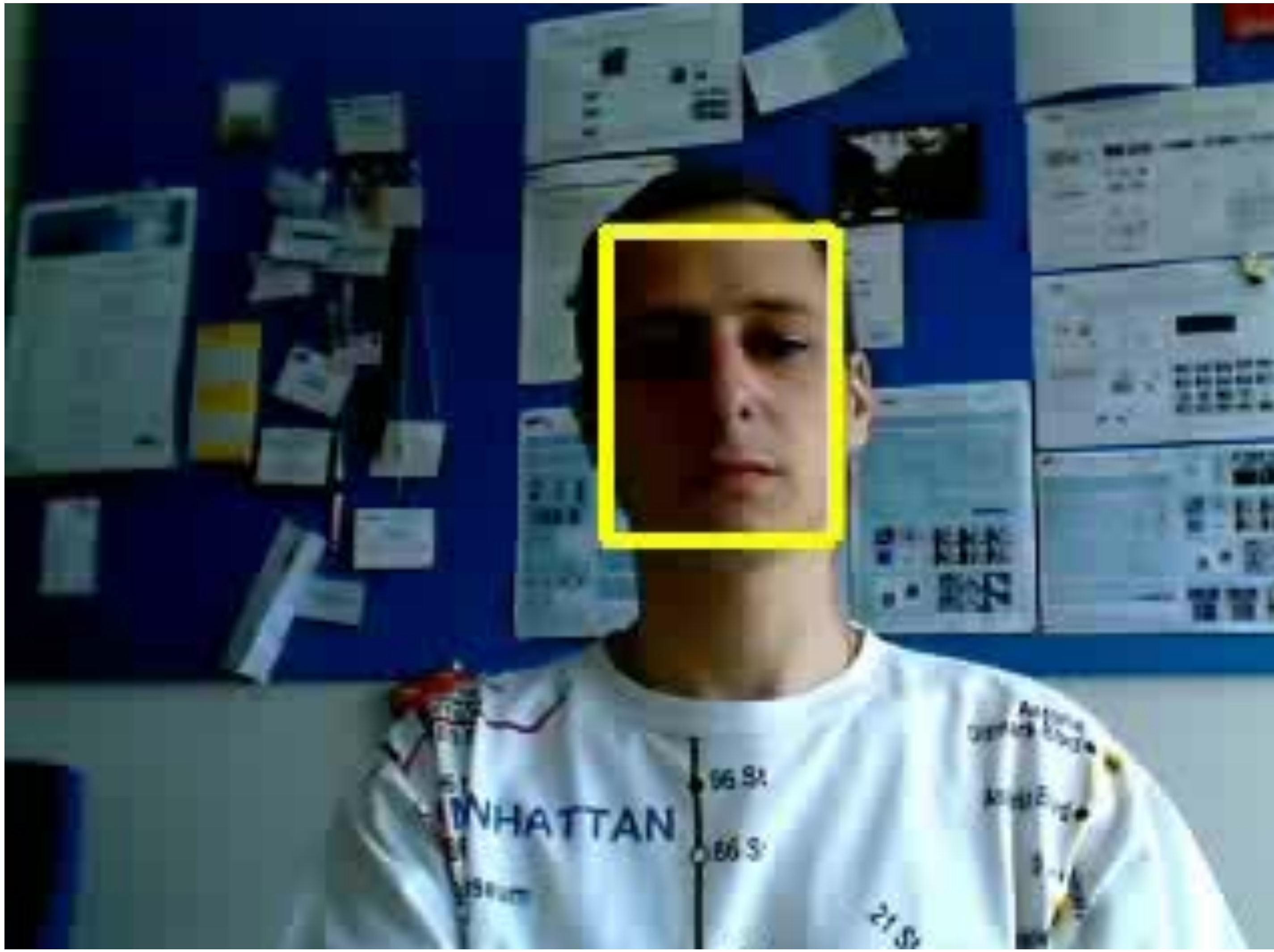
Computer Vision

For tracking “the invisible”



[Grabner et al. CVPR’06]

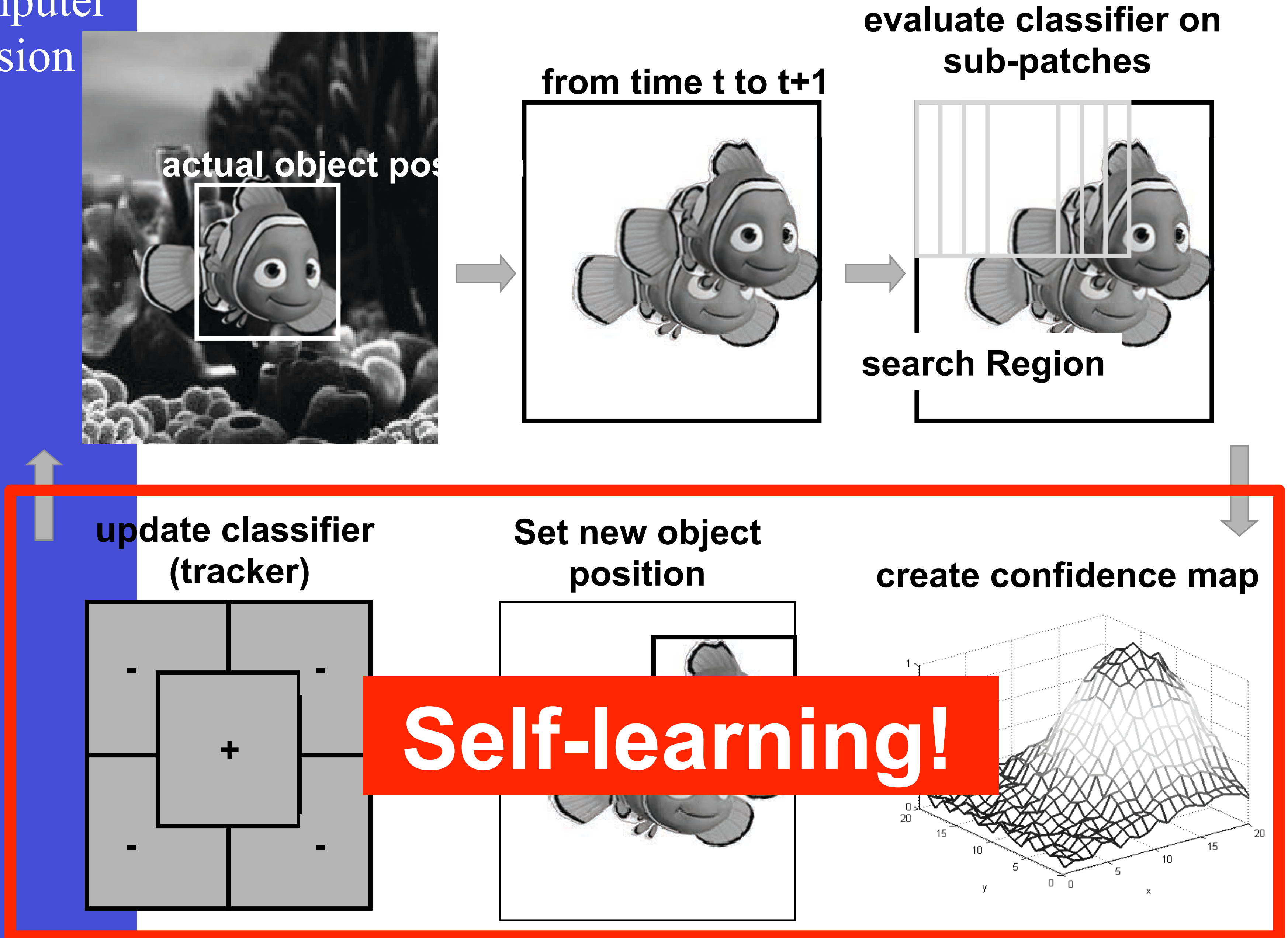
When does it fail…



When does it fail…

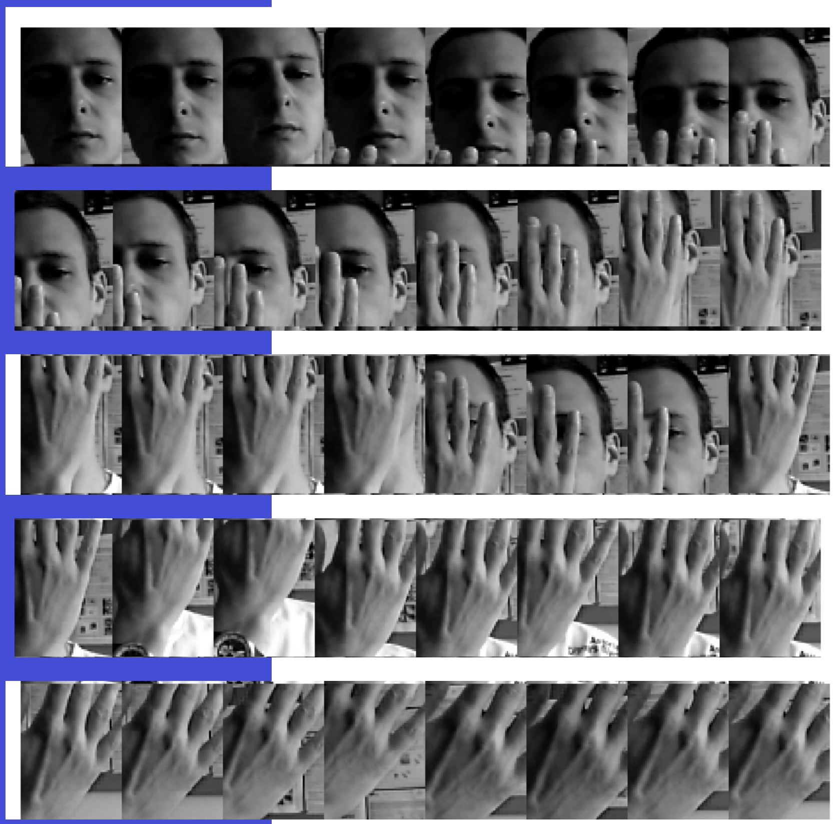
WHY

Computer Vision

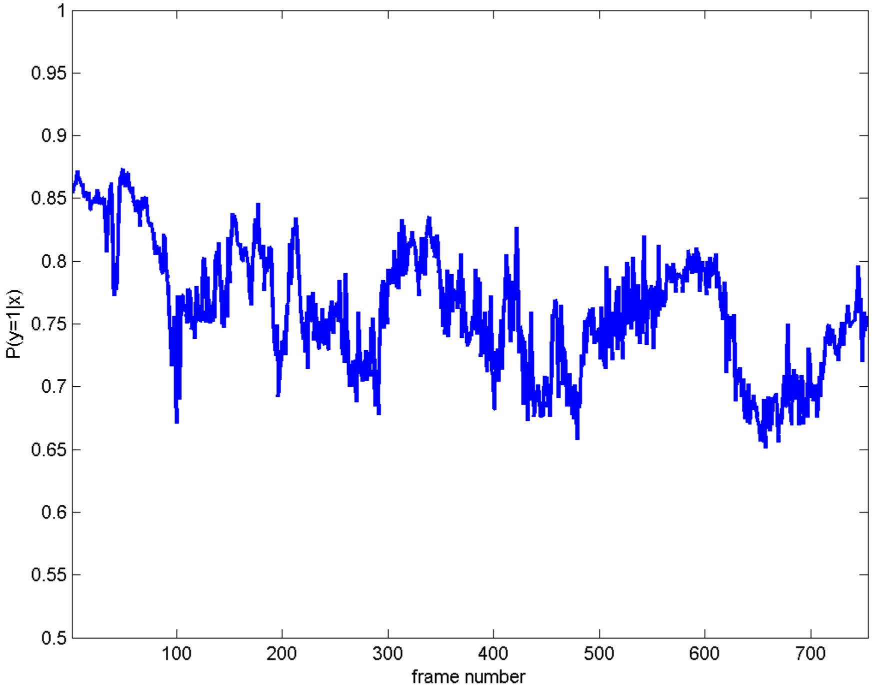


Drift

Tracked Patches

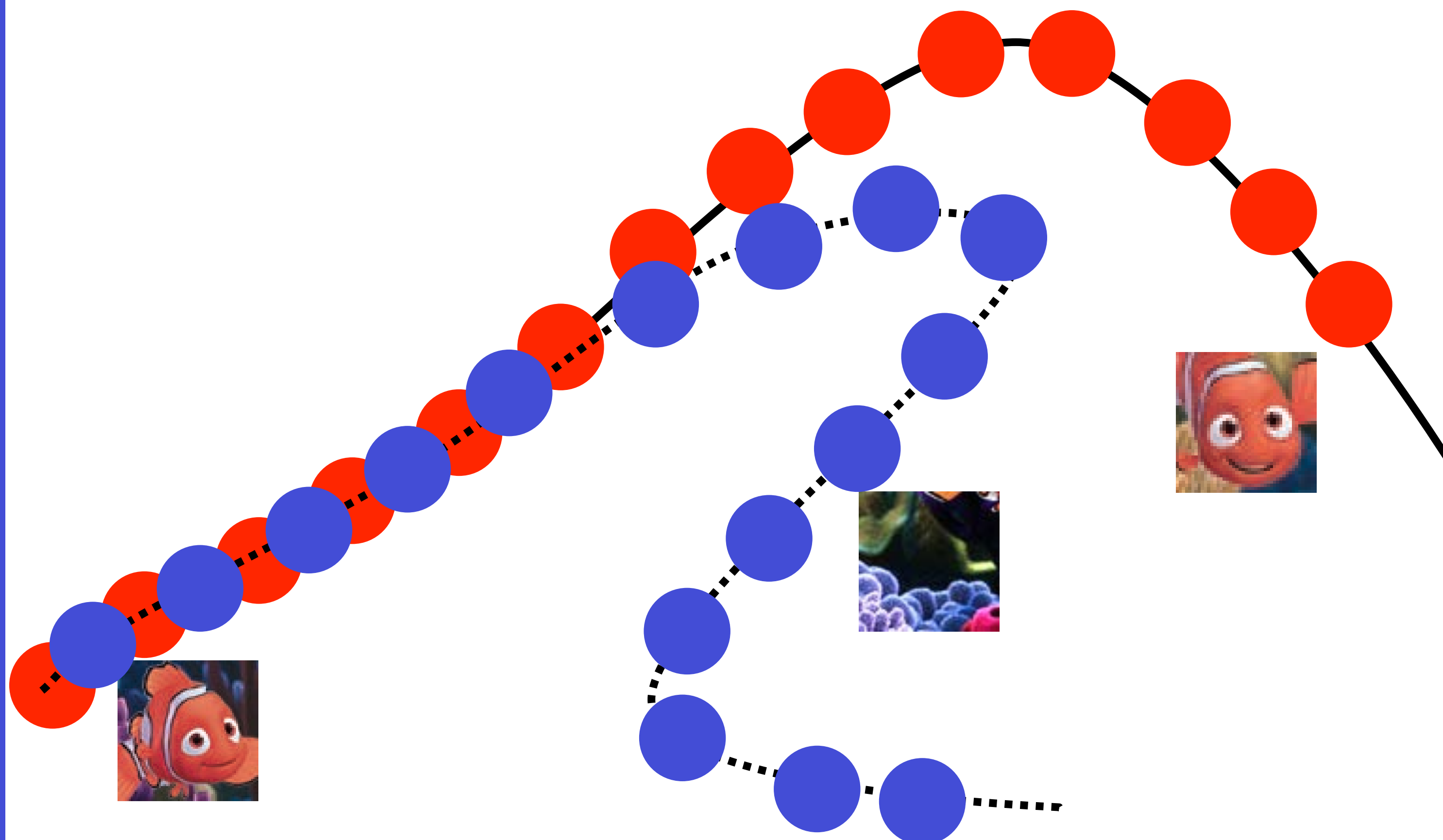


Confidence



Computer Vision

Drift



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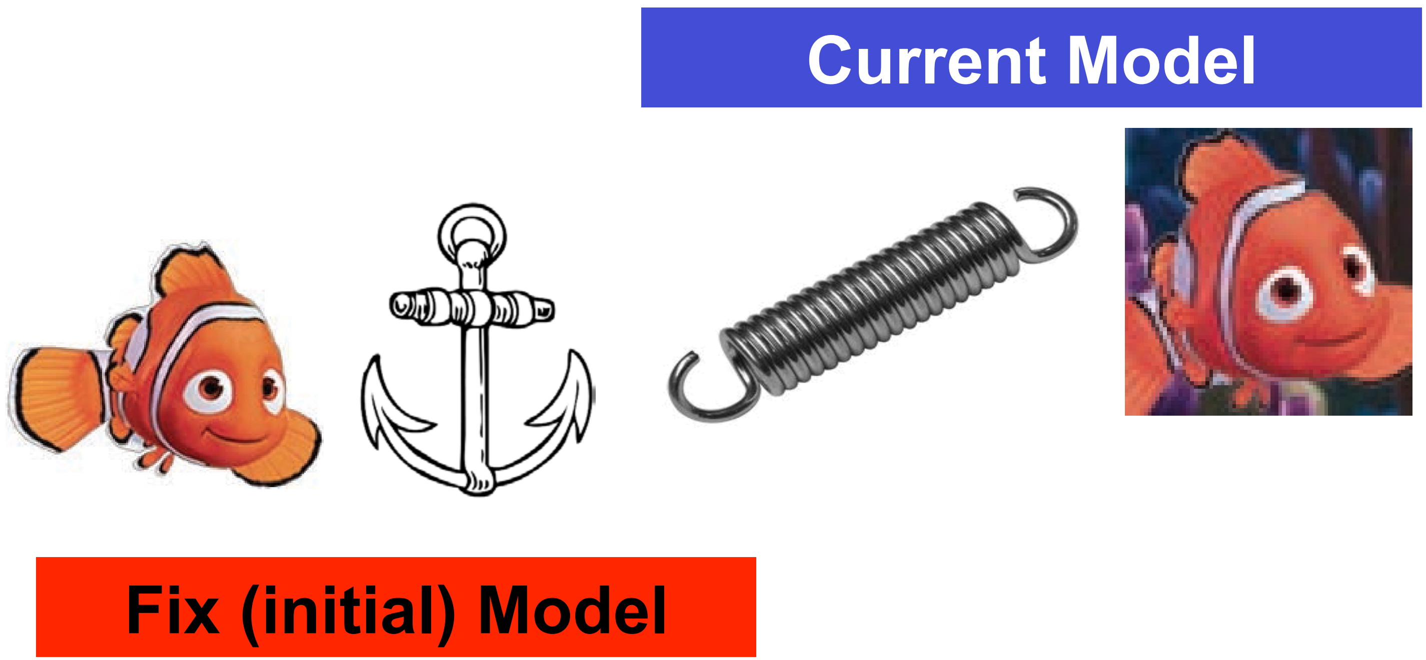
Combining Tracking and Detection

(to avoid drift)

Refining an object model

- Only thing we are sure about the object is its initial model (e.g. appearance in first frame)
- We can “anchor” / correct our model with this information, in order to help avoid drift



Computer Vision

Recover from Drift

using a fixed/anchor model (e.g. first frame)

[Grabner et al. ECCV'08]

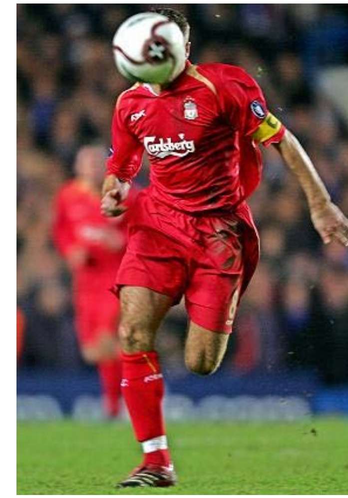
Context in Tracking

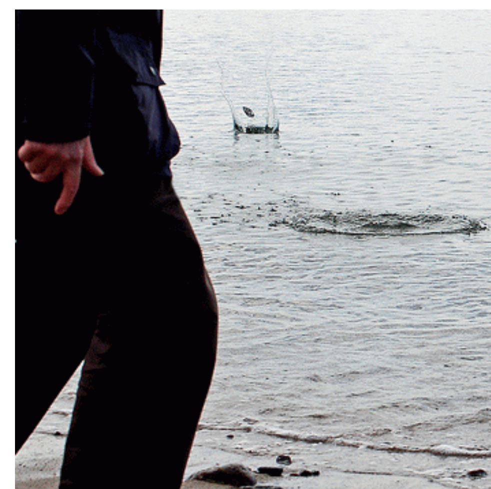
Humans use context to track

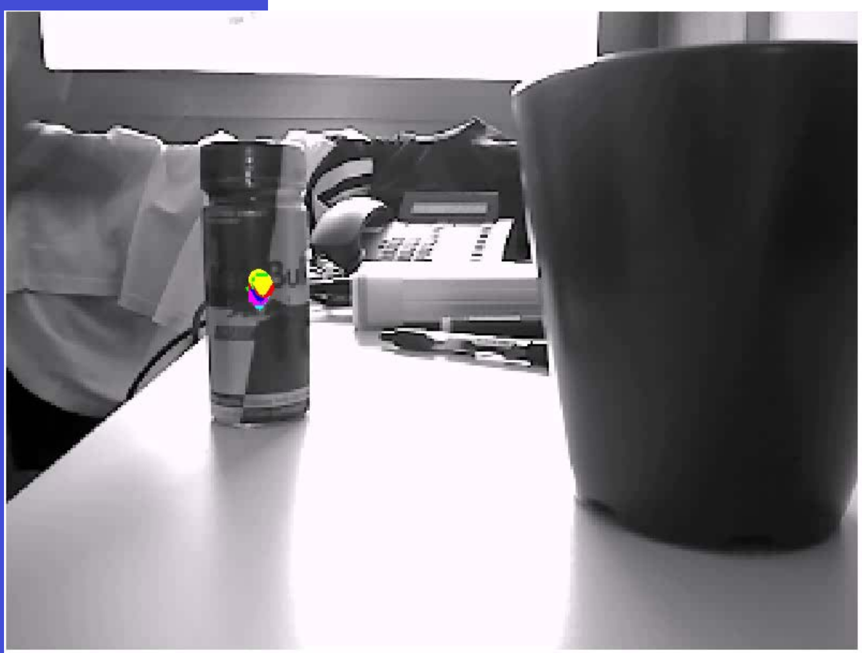
- … objects which change there appearance very quickly.

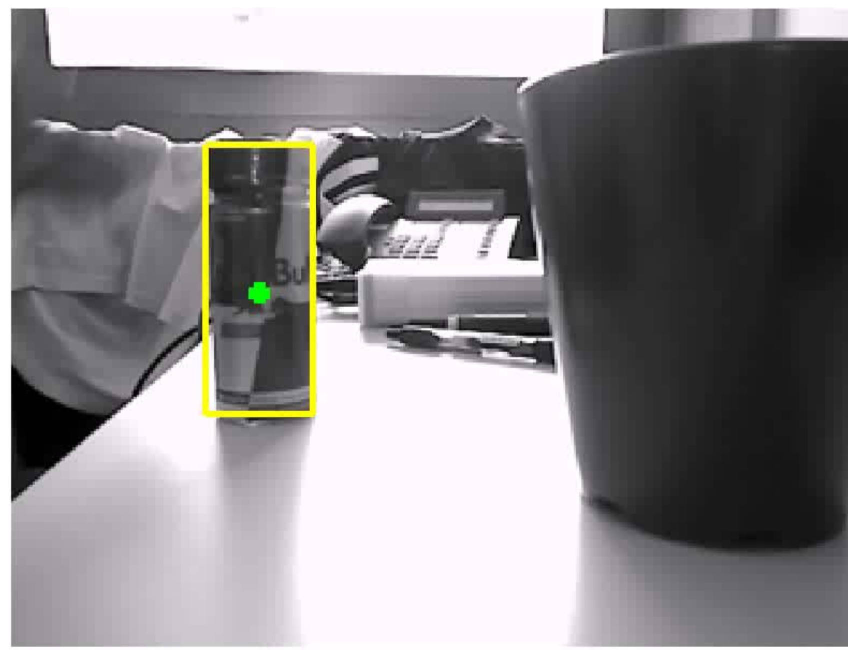
- … occluded objects or object outside the image.

- … small and/or low textured objects or even “virtual points”.

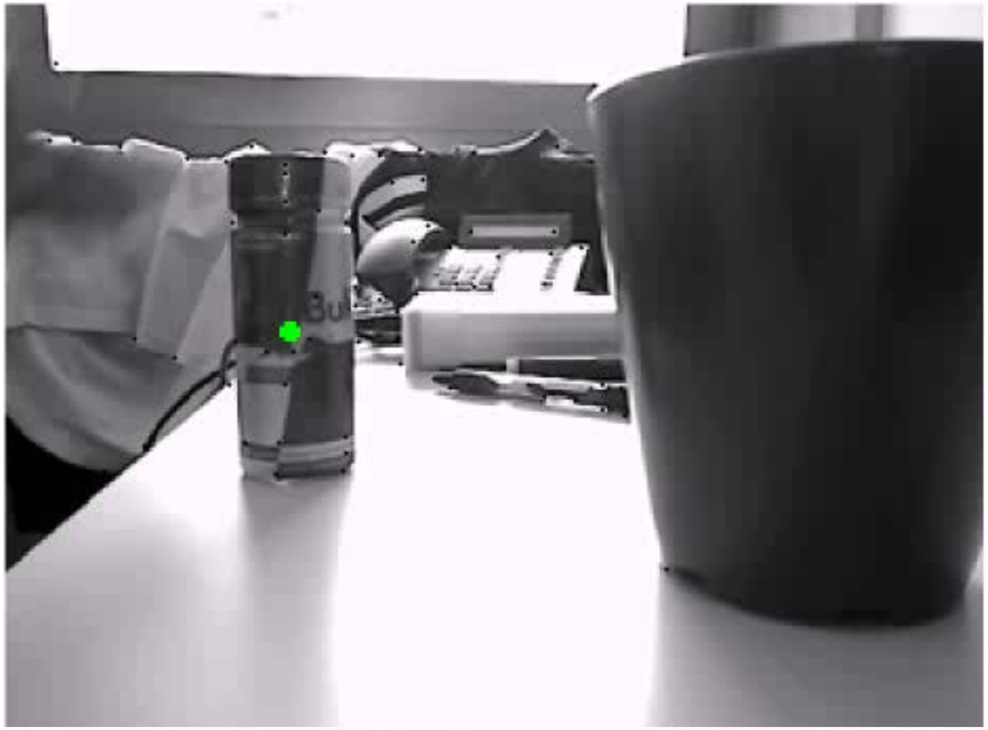








Using Supporters



Computer Vision

Assumptions should hold

With Supporters

In Practice

Which strategy to use?

Depends... No single solution

Some rule-of-thumb suggestions:

- If you can alter the “object” to be tracked,

➔ modify/add tracking info
e.g. optical IR markers, mark with patterns, etc

- If object is fixed/known, but modification not possible/ desired ➔ Utilize known info
  e.g. use a template image and/or known object features

- If object unknown/variable object, but resides in a known (static) environment ➔ bg modeling!

- If none above, simply follow from initial image/location, or use sophisticated learning techniques for detection

Tracking v.s. segmentation/localization:
Key difference is TEMPORAL consistency

Let's apply

Q. What tracking method would you use in each following application scenario?

What limitations you may expect?

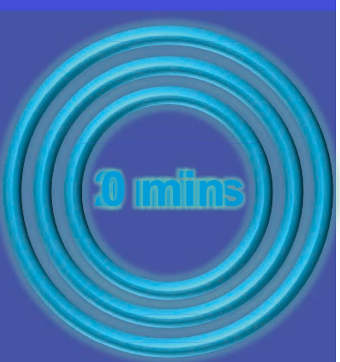
Task: "Discuss one (or more) in groups"

<ins>App1. Safety:</ins> In a lumbar mill, you wish to use CV to stop the blade if a hand reaches nearby.

<ins>App2. Medical:</ins> You wish to track the motion of an ultrasound probe, to relate images in space,.

<ins>App3. Autonomous driving:</ins> Tracking other nearby vehicles to adjust speed and course.

<ins>AppX.</ins> Your favourite tracking app

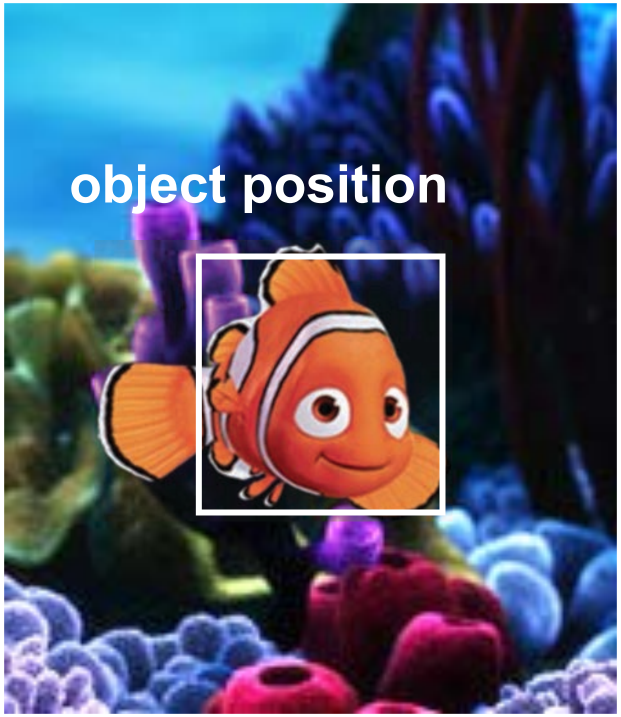


Problems in Tracking

Tracking Issues

- Initialization

Time t = 0



Tracking Issues

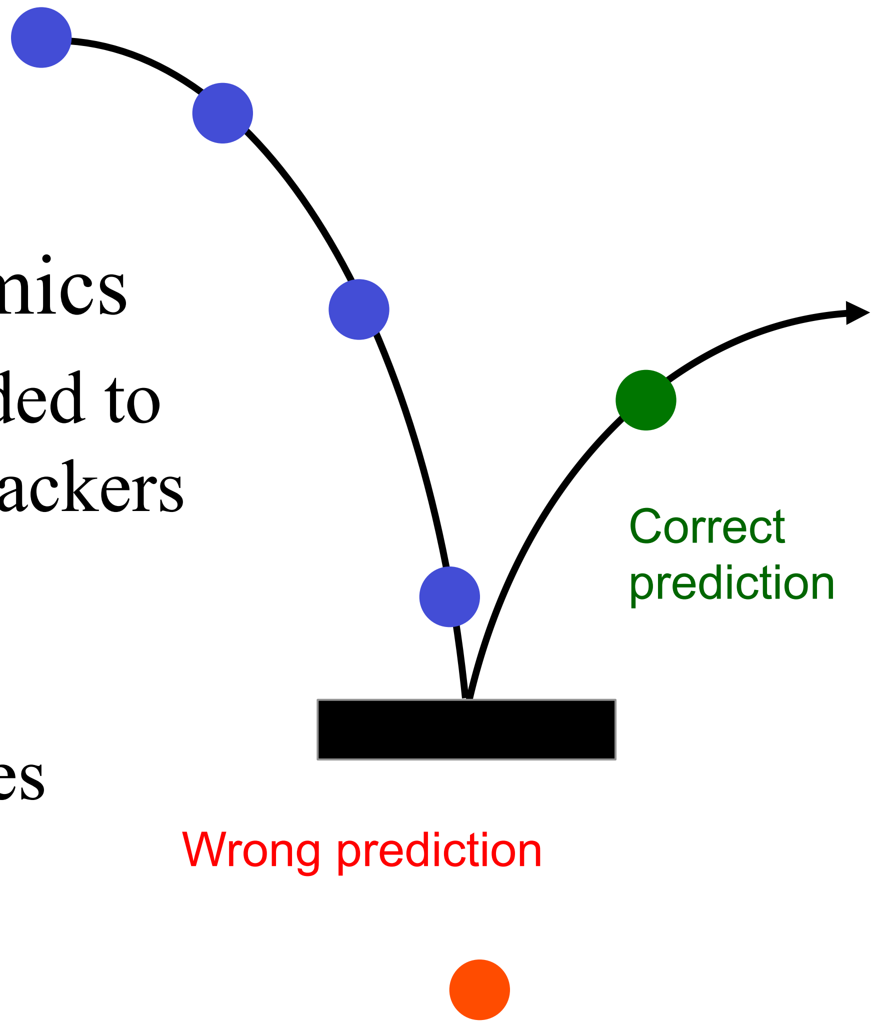
- Obtaining observation…
  - Generative: “render” the state on top of the image and compare
  - Discriminative: classifier or detector score
- …and dynamics model
  - specify using domain knowledge
  - learn (very difficult)

Tracking Issues

- Model- vs. Model-free-Tracking

Tracking Issues

- Nonlinear dynamics
  - Sometimes needed to keep multiple trackers in parallel
  - E.g., for abrupt direction changes („Persons“)



Tracking Issues

- Prediction vs. Correction (cf. Kalman Filtering)
  - If the <u>dynamics</u> model is <u>too strong</u>, tracking will end up <u>ignoring the data</u>.
  - If the <u>observation</u> model is <u>too strong</u>, tracking is <u>reduced to repeated detection</u>.

Tracking Issues

- Data Association –
  Multiple Object Tracking
  - What if we don't know which measurements to associate with which tracks?

Tracking Issues

- Data Association – Occlusions / Self Occlusions

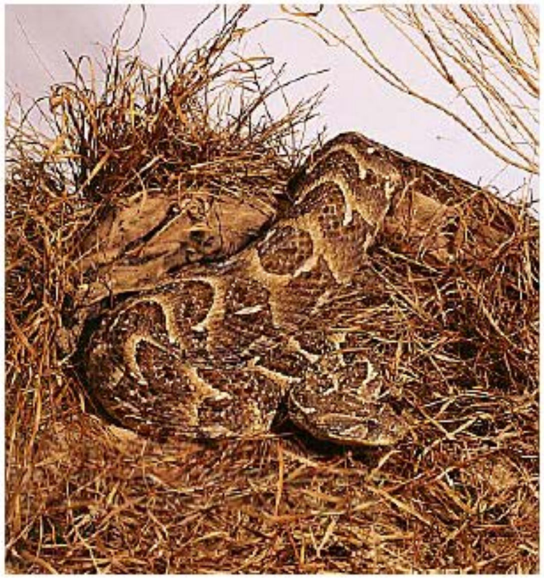
Tracking Issues

- Data Association – Fast Motion

Computer Vision

Tracking Issues

- Data Association – Background / Appearance Change
  - – Cluttered Background
  - – Changes in shape, orientation, color,…



Tracking Issues

- Drift
  - Errors caused by dynamical model, observation model, and data association tend to accumulate over time

Summary

Feature

- Region Tracking (and Mean Shift Algorithm)
- Point Tracking (and Aperture Problem)
- Template Tracking (Lucas-Kanade)

Model

- Tracking-by-Detection
  - a specific target (e.g., keypoints + Ransac)
  - object class (multiple object tracking)
- Model-based Body Articulation
- On-line Learning

- Misc (preventing drift, context, issues)