Computer Vision 2
WS 2018/19

Part 2 – Background Modeling
16.10.2018

Prof. Dr. Bastian Leibe

RWTH Aachen University, Computer Vision Group
http://www.vision.rwth-aachen.de

Announcements: Reminder

- Teaching Assistants
  – Francis Engelmann (engelmann@vision.rwth-aachen.de)
  – Theodora Kontogianni (kontogianni@vision.rwth-aachen.de)
  – Jonathan Luiten (luiten@vision.rwth-aachen.de)
- Course webpage
  – http://www.vision.rwth-aachen.de/courses/
  → Computer Vision2
  – Slides will be made available on the webpage and in the L2P
  – Screencasts of the lecture will be uploaded to L2P
- Please subscribe to the lecture in rwth online!
  – Important to get email announcements and L2P access!

Course Outline

- Single-Object Tracking
  – Background modeling
  – Template based tracking
  – Tracking by online classification
  – Tracking-by-detection
- Bayesian Filtering
- Multi-Object Tracking
- Visual Odometry
- Visual SLAM & 3D Reconstruction
- Deep Learning for Video Analysis

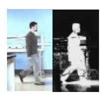
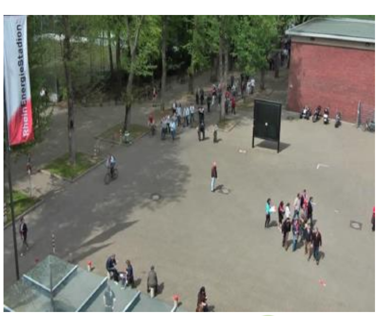


Image source: Tobias Jaeggli

Topics of This Lecture

- Motivation: Background Modeling
- Simple Background Models
  – Background Subtraction
  – Frame Differencing
- Statistical Background Models
  – Single Gaussian
  – Mixture of Gaussians
  – Kernel Density Estimation
- Practical Issues and Extensions
  – Background model update
  – Applications

Motivation: Tracking from Static Cameras



Video source: Wolfgang Mehner

Motivation

- Goals
  – Want to detect and track all kinds of objects in a wide variety of surveillance scenarios.
  ⇒ *Need a general algorithm that works for many scenarios.*
  – Video frames come in at 30Hz. There isn't much time to process them.
  ⇒ *Real-time algorithms need to be very simple.*
- Assumptions
  – The camera is static.
  – Objects that move are important (people, vehicles, etc.).
- Basic Approach
  – Maintain a model of the static background.
  – Compare the current frame to this model to detect objects.

Slide adapted from Robert Collins

Background Modeling Results

Video source: Wolfgang Mehner, Istvan Sarandi

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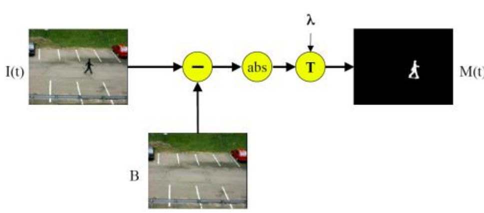
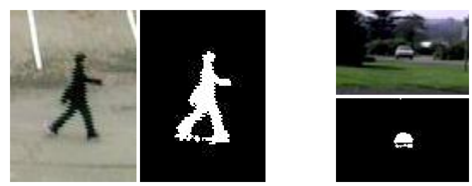
Simple Background Subtraction



- Procedure
  - Background model is a static image (without any objects).
  - Pixels are labeled based on thresholding the absolute intensity difference between current frame and background.

Slide credit: Robert Collins

Background Subtraction Results

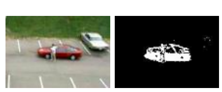


- Observation
  - Background subtraction does a reasonable job of extracting the object shape if the object intensity/color is sufficiently different from the background.
- *What are the limitations of this simple procedure?*

Slide credit: Robert Collins

Background Subtraction: Limitations

- Outdated reference frame
  - Objects that enter the scene and stop continue to be detected...
    ...making it difficult to detect new objects that pass in front of them.



  - If part of the assumed static background starts moving...

    ...both the object and its negative ghost (the revealed background) are detected.

Slide credit: Robert Collins

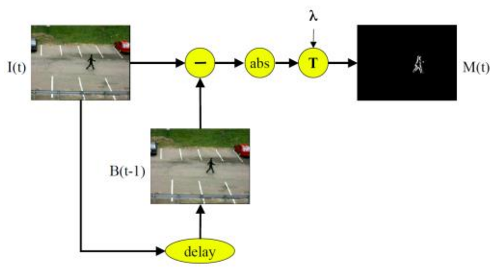
Background Subtraction: Limitations

- Illumination changes
  - Background subtraction is sensitive to illumination changes and unimportant scene motion (e.g., tree branches swaying in the wind).
- Global threshold
  - A single, global threshold for the entire scene is often suboptimal.

$\Rightarrow$ *Need adaptive model with local decisions*

Slide credit: Robert Collins

Simple Frame Differencing



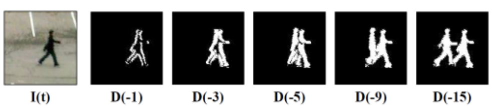
- Other idea
  - Background model is replaced with the previous image.

Frame Differencing Observations

- Advantages
  - Frame differencing is very quick to adapt to changes in lighting or camera motion.
  - Objects that stop are no longer detected.
  - Objects that start up no longer leave behind ghosts.

- Limitations
  - Frame differencing only detects the leading and trailing edge of a uniformly colored object.
  - Very few pixels on the object are labeled.
  - Very hard to detect an object moving towards or away from the camera.

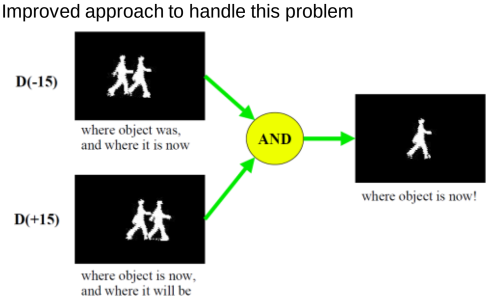
Differencing and Temporal Scale



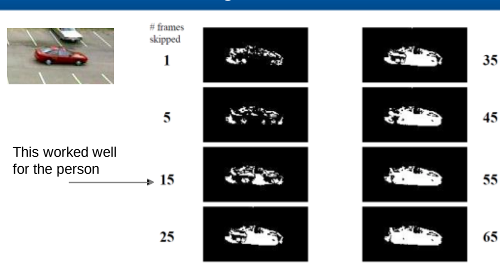
- More general formulation
  - Define $D(N) = \|I(t) - I(t+N)\|$
- Effect of increasing the temporal scale
  - More complete object silhouette, but two copies of the object (one where it used to be, one where it is now).

Three-Frame Differencing

- Improved approach to handle this problem

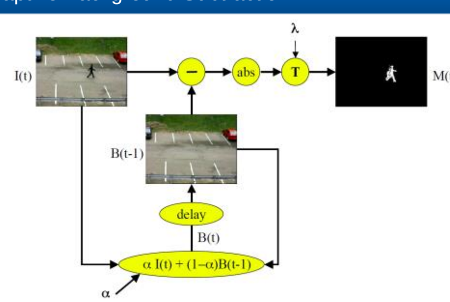


Three-Frame Differencing



- Problem
  - Choice of good frame-rate for three-frame differencing depends on size and speed of object.

Adaptive Background Subtraction



- Current image is "blended" into the background model with α.

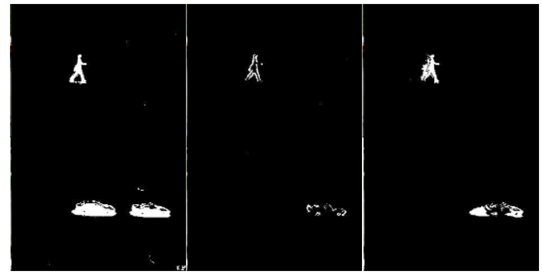
Adaptive Background Subtraction

- Properties
  - More responsive to changes in illumination and camera motion.
  - Small, fast-moving objects are well-segmented, but they leave behind short "trails" of pixels.
  - Objects that stop and ghosts left behind by objects that start both gradually fade into the background.
  - The centers of large, slow-moving objects start to fade into the background, too!
  - This can be fixed by decreasing the blend parameter α, but then it takes longer for ghost objects to disappear...



Slide credit: Robert Collins

Comparisons



BG Subtraction | Frame Differencing | Adaptive BG Subtract.

Slide adapted from Robert Collins

Discussion

- Background subtraction / Frame differencing
  - Very simple techniques, historically among the first.
  - Straight-forward to implement, fast to test out.
  - We've seen some fixes for the most pressing problems.
- Remaining limitations
  - Rather heuristic approach.
  - Leads to relatively poor foreground/background decisions.
  - Optimal temporal scale still depends on object size and speed.
  - Global threshold is often suboptimal for parts of the image.

  $\Rightarrow$ *Very fiddly in practice, requires extensive parameter tuning.*
- Let's try to come up with a better founded approach
  - Using a statistical model of background probability...

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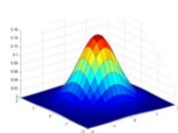
Gaussian Background Model

- Statistical model
  - Value of a pixel represents a measurement of the radiance of the first object intersected by the pixel's optical ray.
  - With a static background and static lighting, this value will be a constant affected by i.i.d. Gaussian noise.



- Idea
  - Model the background distribution of each pixel by a single Gaussian centered at the mean pixel value:

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right\}$$

  - Test if a newly observed pixel value has a high likelihood under this Gaussian model.

$\Rightarrow$ *Automatic estimation of a sensitivity threshold for each pixel.*

Recap: Maximum Likelihood Approach

- Computation of the likelihood
  - Single data point: $p(x_n|\theta)$
  - Assumption: all data points $X = \{x_1, \ldots, x_n\}$ are independent

$$L(\theta) = p(X|\theta) = \prod_{n=1}^{N} p(x_n|\theta)$$

  - (Negative) Log-likelihood

$$E(\theta) = -\ln L(\theta) = -\sum_{n=1}^{N} \ln p(x_n|\theta)$$

- Estimation of the parameters θ (Learning)
  - Maximize the likelihood (=minimize the negative log-likelihood)

  $\Rightarrow$ Take the derivative and set it to zero.

$$\frac{\partial}{\partial\theta}E(\theta) = -\sum_{n=1}^{N} \frac{\frac{\partial}{\partial\theta}p(x_n|\theta)}{p(x_n|\theta)} \stackrel{!}{=} 0$$

Recap: Maximum Likelihood Approach

- For a 1D Gaussian, we thus obtain

$$\hat{\mu} = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad \text{“sample mean”}$$

- In a similar fashion, we get

$$\hat{\sigma}^2 = \frac{1}{N}\sum_{n=1}^{N} (x_n - \hat{\mu})^2 \qquad \text{“sample variance”}$$

- $\hat{\theta} = (\hat{\mu}, \hat{\sigma})$ is the Maximum Likelihood estimate for the parameters of a Gaussian distribution.
- Note: the estimate of the sample variance is *biased*. Better use

$$\tilde{\sigma}^2 = \frac{1}{N-1}\sum_{n=1}^{N} (x_n - \hat{\mu})^2$$

Online Adaptation (1D Case)

- Once estimated, adapt the Gaussians over time
  - We can compute a running estimate over a time window

$$\hat{\mu}^{(t+1)} = \hat{\mu}^{(t)} + \frac{1}{N}x^{(t+1)} - \frac{1}{N}x^{(t+1-T)}$$

$$(\tilde{\sigma}^2)^{(t+1)} = (\tilde{\sigma}^2)^{(t)} + \frac{1}{N-1}(x^{(t+1)} - \hat{\mu}^{(t+1)})^2 - \frac{1}{N-1}(x^{(t+1-T)} - \hat{\mu}^{(t+1)})^2$$

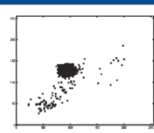
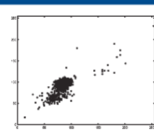
  - However, the distribution is non-stationary (and newer values are more important) $\Rightarrow$ better use an Exponential Moving Average filter

$$\hat{\mu}^{(t+1)} = (1-\alpha)\hat{\mu}^{(t)} + \alpha x^{(t+1)}$$

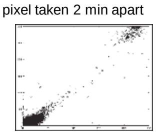
$$(\tilde{\sigma}^2)^{(t+1)} = (1-\alpha)(\tilde{\sigma}^2)^{(t)} + \alpha(x^{(t+1)} - \hat{\mu}^{(t+1)})^2$$

with a fixed learning rate α.

Problem: Complex Distributions

RG scatter plots of the same pixel taken 2 min apart

Bi-modal distribution caused by specularities on the water surface

$\Rightarrow$ *A single Gaussian is clearly insufficient here...*

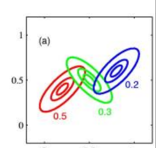
Image source: Chris Stauffer

Problem: Adaptation Speed, Sensitivity

- If the background model adapts too slowly...
  - Will construct a very wide and inaccurate model with low detection sensitivity
- If the model adapts too quickly...
  - Leads to inaccurate estimation of the model parameters
  - The model may adapt to the targets themselves (especially slow-moving ones)
- Design trade-off
  - Model should adapt quickly to changes in the background process *and* detect objects with high sensitivity.
  - *How can we achieve that?*

MoG Background Model

- Improved statistical model
  - Large jumps between different pixel values because different objects are projected onto the same pixel at different times.
  - While the same object is projected onto the pixel, small local intensity variations due to Gaussian noise.



- Idea
  - Model the color distribution of each pixel by a mixture of K Gaussians

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

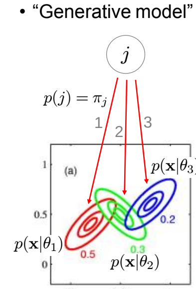
  - Evaluate likelihoods of observed pixel values under this model.
  - Or let entire Gaussian components adapt to foreground objects and classify components as belonging to object or background.

Image source: Chris Bischop

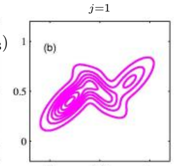
Recap: Mixtures of Gaussians

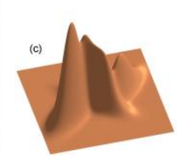
- “Generative model”

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$



$$p(\mathbf{x}|\theta) = \sum_{j=1}^{3} \pi_j p(\mathbf{x}|\theta_j)$$





Slide credit: Bernt Schiele
Image source: C.M. Bishop, 2006

Recap: EM Algorithm

- Expectation-Maximization (EM) Algorithm
  - E-Step: softly assign samples to mixture components

$$\gamma_j(\mathbf{x}_n) \leftarrow \frac{\pi_j \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}{\sum_{k=1}^{N} \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)} \qquad \forall j = 1,\dots,K, \quad n = 1,\dots,N$$

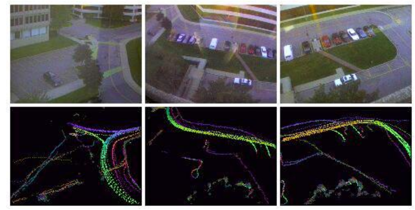
  - M-Step: re-estimate the parameters (separately for each mixture component) based on the soft assignments

$$\hat{\pi}_j^{\text{new}} \leftarrow \frac{\hat{N}_j}{N} \qquad \hat{N}_j \leftarrow \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n) \text{ = soft \#samples labeled } j$$

$$\hat{\boldsymbol{\mu}}_j^{\text{new}} \leftarrow \frac{1}{\hat{N}_j} \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n)\mathbf{x}_n$$

$$\hat{\boldsymbol{\Sigma}}_j^{\text{new}} \leftarrow \frac{1}{\hat{N}_j} \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n)(\mathbf{x}_n - \hat{\boldsymbol{\mu}}_j^{\text{new}})(\mathbf{x}_n - \hat{\boldsymbol{\mu}}_j^{\text{new}})^{\mathrm{T}}$$

Stauffer-Grimson Background Model



- Very popular model
  - Used in many tracking approaches
  - Suitable for long-term observations (finding patterns of activity)

C. Stauffer, W.E.L. Grimson, Adaptive Background Mixture Models for Real-Time Tracking, CVPR 1998.

Stauffer-Grimson Background Model

- Idea
  - Model the distribution of each pixel by a mixture of K Gaussians

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \quad \text{where} \quad \boldsymbol{\Sigma}_k = \sigma_k^2 \mathbf{I}$$

  - Check every new pixel value against the existing K components until a match is found (pixel value within $2.5\ \sigma_k$ of μ_k).
  - If a match is found, adapt the corresponding component.
  - Else, replace the least probable component by a distribution with the new value as its mean and an initially high variance and low prior weight.
  - Order the components by the value of w_k/σ_k and select the best B components as the background model, where

$$B = \arg\min_b \left(\sum_{k=1}^{b} \frac{w_k}{\sigma_k} > T \right)$$

Stauffer-Grimson Background Model

- Online adaptation
  - Instead of estimating the MoG using EM, use a simpler online adaptation, assigning each new value only to the matching component.
  - Let $M_{k,t} = 1$ iff component k is the model that matched, else 0.

$$\pi_k^{(t+1)} = (1-\alpha)\pi_k^{(t)} + \alpha M_{k,t}$$

  - Adapt only the parameters for the matching component

$$\boldsymbol{\mu}_k^{(t+1)} = (1-\rho)\boldsymbol{\mu}_k^{(t)} + \rho x^{(t+1)}$$

$$\boldsymbol{\Sigma}_k^{(t+1)} = (1-\rho)\boldsymbol{\Sigma}_k^{(t)} + \rho(x^{(t+1)} - \boldsymbol{\mu}_k^{(t+1)})(x^{(t+1)} - \boldsymbol{\mu}_k^{(t+1)})^T$$

where

$$\rho = \alpha \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

(i.e., the update is weighted by the component likelihood)

Discussion: Stauffer-Grimson Model

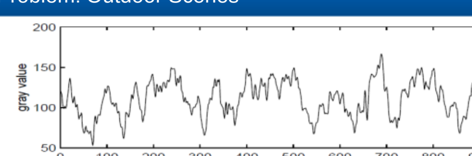
- Properties
  - Static foreground objects can be integrated into the mixture
    - Advantage: This doesn't destroy the existing background model.
    - If an object is stationary for some time and then moves again, the distribution for the background still exists

    ⇒ Quick recovery from such situations.
  - Ordering of components by w_k/σ_k
    - Favors components that have more evidence (higher w_k) and a smaller variance (lower σ_k).

    ⇒ Those are typically the best candidates for background.
  - Model can adapt to the complexity of the observed distribution.
    - If the distribution is unimodal, only a single component will be selected for the background.

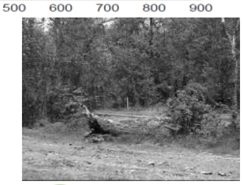
    ⇒ This can be used to save memory and computation.

Problem: Outdoor Scenes



- Dynamic areas
  - Waving trees, rippling water, ...
  - Fast variations

⇒ *More flexible representation needed here.*



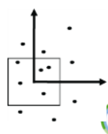
Recap: Kernel Density Estimation

- Estimating the probability density from discrete samples
  - Approximation: $p(\mathbf{x}) \approx \frac{K}{NV}$

fixed V determine K → Kernel Methods

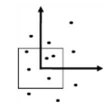
fixed K determine V → K-Nearest Neighbor

- Kernel methods
  - Example: Determine the number K of data points inside a fixed hypercube…



Recap: Kernel Density Estimation

- Parzen Window
  - Hypercube of dimension D with edge length h:



$$k(\mathbf{u}) = \begin{cases} 1, & |u_i| \leq \frac{1}{2}, \quad i = 1, \dots, D \\ 0, & else \end{cases}$$

"Kernel function"

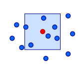
$$K = \sum_{n=1}^{N} k\left(\frac{\mathbf{x} - \mathbf{x}_n}{h}\right) \qquad V = \int k(\mathbf{u}) d\mathbf{u} = h^d$$

  - Probability density estimate:

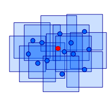
$$p(\mathbf{x}) \approx \frac{K}{NV} = \frac{1}{Nh^D} \sum_{n=1}^{N} k\left(\frac{\mathbf{x} - \mathbf{x}_n}{h}\right)$$

Recap: Parzen Window

- Interpretations
  1. We place a *kernel window k at location $\mathbf{x}$* and count how many data points fall inside it.



  2. We place a *kernel window k around each data point $\mathbf{x}_n$* and sum up their influences at location $\mathbf{x}$.



  ⇒ Direct visualization of the density.

- Still, we have artificial discontinuities at the cube boundaries…
  - We can obtain a smoother density model if we choose a smoother kernel function, e.g. a Gaussian

Kernel Background Modeling

- Nonparametric model of background appearance
  - Very flexible approach, can deal with large amounts of background motion and scene clutter

A. Elgammal, D. Harwood, L.S. Davis, Non-parametric Model for Background Subtraction, ECCV 2000.

Video source: Ahmed Elgammal

Kernel Background Modeling

- Nonparametric density estimation
  - Estimate a pixel's background distribution using the kernel density estimator $K(\cdot)$ as

$$p(\mathbf{x}^{(t)}) = \frac{1}{N} \sum_{i=1}^{N} K(\mathbf{x}^{(t)} - \mathbf{x}^{(i)})$$

  - Choose K to be a Gaussian $\mathcal{N}(0, \mathbf{\Sigma})$ with $\mathbf{\Sigma} = \mathrm{diag}\{\sigma_j\}$. Then

$$p(\mathbf{x}^{(t)}) = \frac{1}{N} \sum_{i=1}^{N} \prod_{j=1}^{d} \frac{1}{\sqrt{2\pi\sigma_j^2}} e^{-\frac{1}{2}\frac{(x_j^{(t)} - x_j^{(i)})^2}{\sigma_j^2}}$$

  - A pixel is considered foreground if $p(\mathbf{x}^{(t)}) < \theta$ for a threshold θ.
    - This can be computed very fast using lookup tables for the kernel function values, since all inputs are discrete values.
    - Additional speedup: partial evaluation of the sum usually sufficient

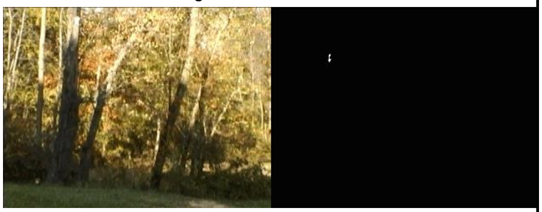
Results Kernel Background Modeling

- Performance in heavy rain

Video source: Ahmed Elgammal

Results Kernel Background Modeling

- Results for color images



- Practical issues with color images
  - *Which color space to use?*

Video source: Ahmed Elgammal

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Practical Issues: Background Model Update

- Kernel background model
  - Sample N intensity values taken over a window of W frames.
- FIFO update mechanism
  - Discard oldest sample.
  - Choose new sample randomly from each interval of length W/N frames.
- When should we update the distribution?
  - Selective update: add new sample only if it is classified as a background sample
  - Blind update: always add the new sample to the model.

Updating Strategies

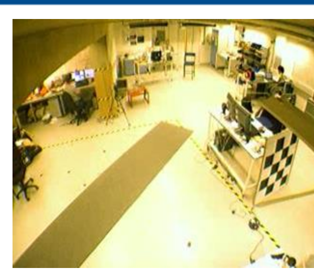
- Selective update
  - Add new sample only if it is classified as a background sample.
  - Enhances detection of new objects, since the background model remains uncontaminated.
  - But: Any incorrect detection decision will result in persistent incorrect detections later.
  - $\Rightarrow$ Deadlock situation.
- Blind update
  - Always add the new sample to the model.
  - Does not suffer from deadlock situations, since it does not involve any update decisions.
  - But: Allows intensity values that do not belong to the background to be added to the model.
  - $\Rightarrow$ Leads to bad detection of the targets (more false negatives).

Solution: Combining the Two Models

- Short-term model
  - Recent model, adapts to changes quickly to allow very sensitive detection
  - Consists of the most recent N background sample values.
  - Updated using a selective update mechanism based on the detection mask from the final combination result.
- Long-term model
  - Captures a more stable representation of the scene background and adapts to changes slowly.
  - Consists of N samples taken from a much larger time window.
  - Updated using a blind update mechanism.
- Combination
  - Intersection of the two model outputs.

[A. Elgammal, D. Harwood, L. Davis, ECCV'00]

Applications: Visual Surveillance



- Background modeling to detect objects for tracking
  - Extension: Learning a foreground model for each object.

Video source: Ian Reid, Univ. of Oxford

Applications: Articulated Tracking

- Background modeling as preprocessing step
  - Track a person's location through the scene
  - Extract silhouette information from the foreground mask.
  - Perform body pose estimation based on this mask.

Video source: Hedvik Kjellstroem, Tobias Jaegol

Summary

- Background Modeling
  - Fast and simple procedure to detect moving object in static camera footage.
  - Makes subsequent tracking *much* easier!
  - ⇒ *If applicable, always make use of this information source!*
- We've looked at two models in detail
  - Adaptive MoG model (Stauffer-Grimson model)
  - Kernel background model (Elgammal et al.)
  - Both perform well in practice, have been used extensively.
- Many extensions available
  - Learning object-specific foreground color models
  - Background modeling for moving cameras

Outlook

- Next lecture
  - Wed: Template-based Tracking

Image source: Robert Collins

References and Further Reading

- More information on density estimation in Bishop's book
  - Gaussian distribution and ML: Ch. 1.2.4 and 2.3.1-2.3.4.
  - Mixture of Gaussians: Ch. 2.3.9 and 9
  - Nonparametric methods: Ch. 2.5.
- More information on background modeling:
  - Visual Analysis of Humans: Ch. 3
  - C. Stauffer et al., Adaptive Background Models for Real-Time Tracking, CVPR'98
  - A. Elgammal et al., Non-parametric Model for Background Subtraction, ECCV'00

Christopher M. Bishop
Pattern Recognition and Machine Learning
Springer, 2006

T. Moeslund, A. Hilton, V. Krueger, L. Sigal
Visual Analysis of Humans: Looking at People
Springer, 2011