Adaptive background mixture models for real-time tracking

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Improving Background Subtraction

- Adaptive Background Mixture Models for Real Time Tracking
  - Chris stauffer and W.E.L. Grimson
  - Over 4000 citations since 1999

Motivation

- Robust background subtraction should handle lighting changes, repetitive motion from clutter and long term scene changes

- Standard method of adaptive background (Adv)
  - It is effective where object moves continuously
  - Background is visible a significant portion of the time

Motivation

- Standard method of adaptive background (Disadv)
  - It is not robust to scenes with many moving objects particularly if they move very slowly
  - http://www.youtube.com/watch?v=YA_lWWhePW8

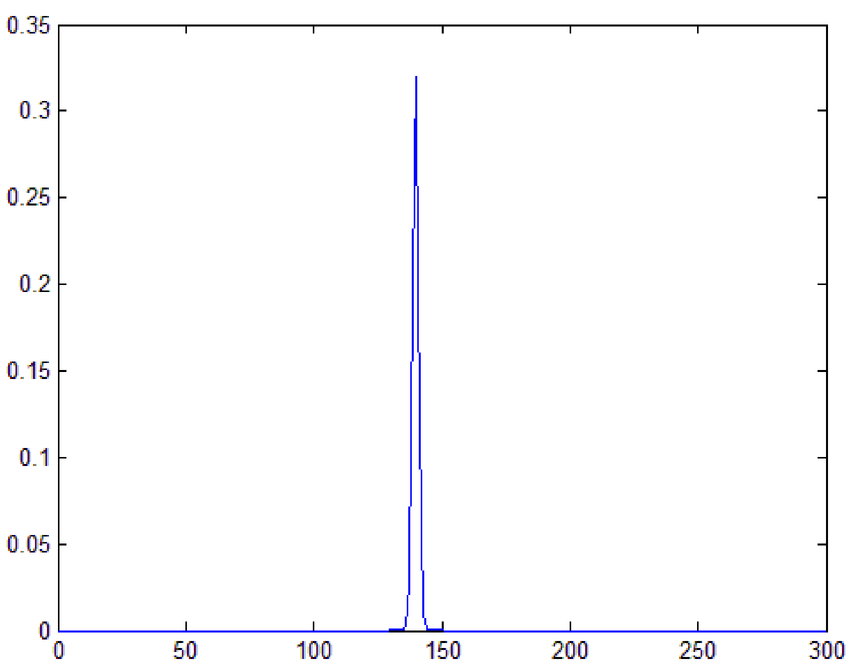
- Recovers slowly when background is uncovered
- It has single predetermined threshold for the entire scene

Motivation

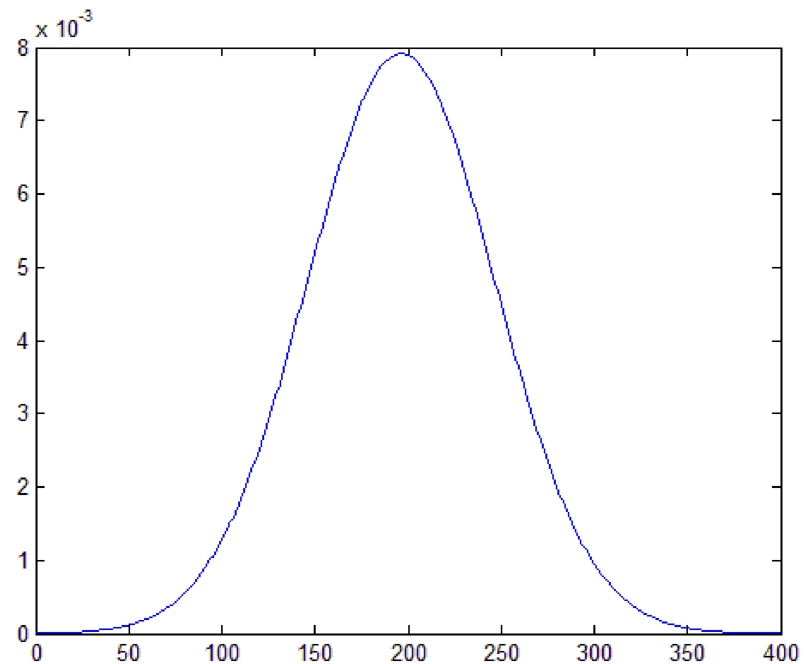
- Standard method of adaptive background (Disadv)
  - It can not handle bimodal backgrounds
  - Assume rainy situation
  - pixel intensity values of background for 16 frames :
    - 139,140,141,141,138,140,140,139,240,241,243,244,180,141 ,140,142
    - Modeling background for each 8 frame with Gaussian distribution
    - $\mu_1=139.75$, $\delta_1=1.22$
    - $\mu_2=196.37$, $\delta_2=50.43$

Motivation

- 139,140,141,141,138,140,140,139,240,241,243,244,180,141,140 ,142



μ_1=139.75, δ_1=1.22



μ_2=196.37, δ_2=50.43

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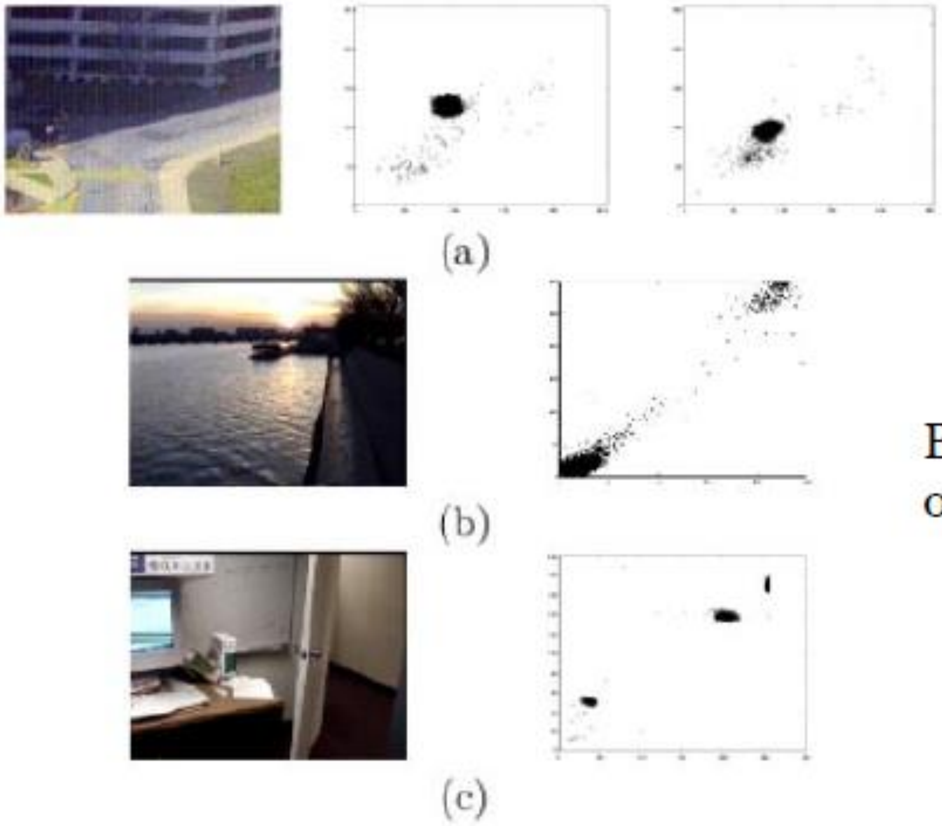
Motivation

RG plots of a single pixel



Differing threshold over time

Bimodal distribution over time

Approach

- Modeling the values of a particular pixel as a mixture of Gaussians
- Based on the persistence and the variance of each Gaussians of the mixture, we determine which Gaussians may correspond to background color
- Pixel values that do not fit the background distributions are considered foreground

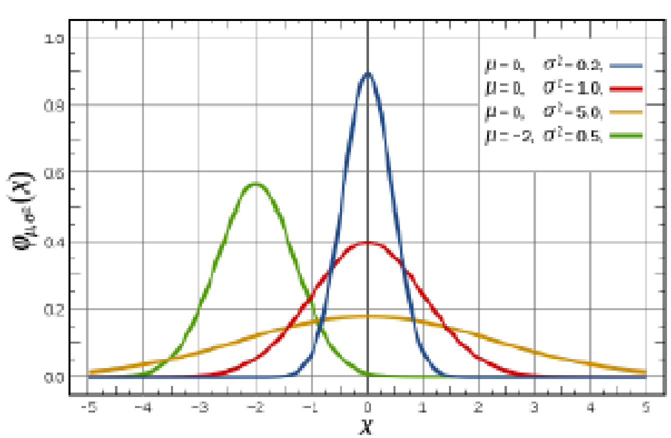
Gaussian Distribution

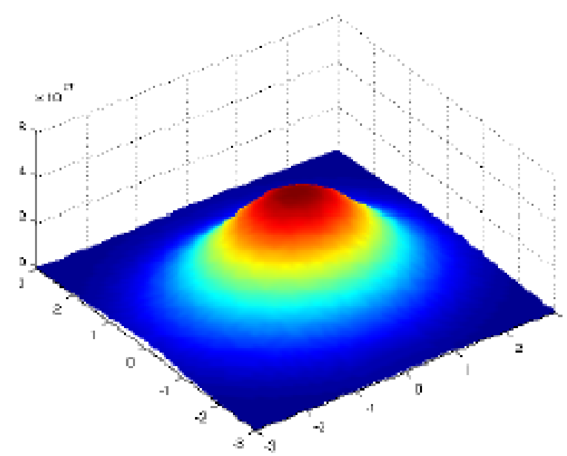
- Univariate

$$\mathcal{N}(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- Multivariate

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





Online Mixture Model

- History of a pixel is known up to current time t

$$\{X_1, \dots, X_t\} = \{I(x_o, y_o, i): 1 \le i \le t\}$$

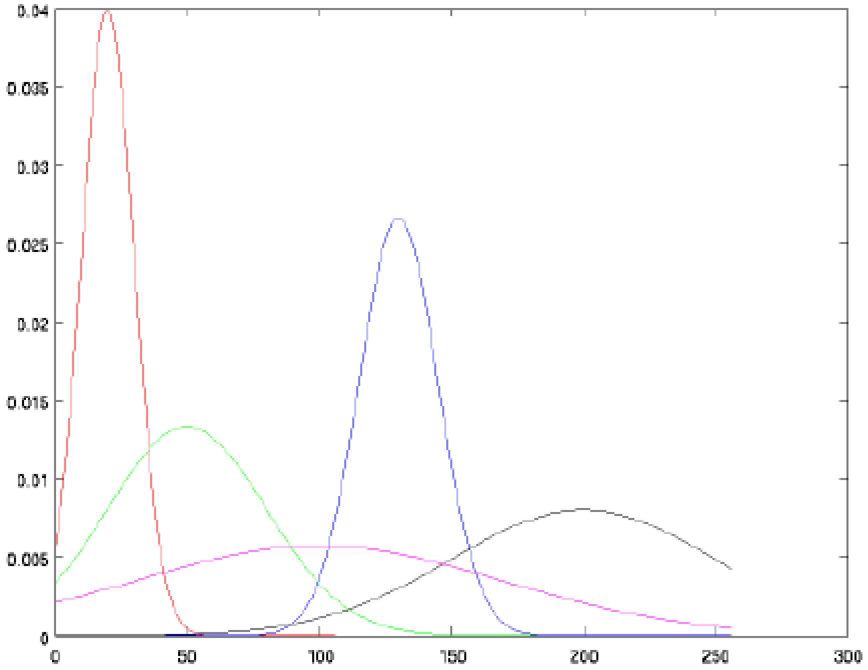
- Model the history as mixture of K Gaussian Distributions

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} \mathcal{N}(X_t | u_{i,t}, \Sigma_{i,t})$$

$w_{i,t}$ - prior probability (weight) of Gaussians i

Mixture Model Example

- For grayscale image with K=5



Update the Mixture Model (Stage 1)

- Every new pixel value, X_{t+1}, is checked against the existing K Gaussian distributions until a match is found.
- A match is defined as a pixel value within 2.5 standard deviations of a distribution

Stage 2

- Match

$$\mu_{i,t+1} = (1-\rho)\mu_{i,t} + \rho X_{t+1}$$
$$\sigma^2_{i,t+1} = (1-\rho)\sigma^2_{i,t} + \rho\left(X_{t+1} - \mu_{i,t}\right)^2$$

  - $\rho = \alpha \mathcal{N}\left(X_{t+1} \middle| \mu_{i,t}, \sigma^2_{i,t}\right)$
  - α – is a learning rate

- Prior weights of Gaussians are updated

$$w_{i,t+1} = (1-\alpha)w_{i,t} + \alpha\left(M_{i,t+1}\right)$$

$M_{i,t+1} = 1$ for matching Guassian or $M_{i,t+1} = 0$ for all others

Stage 3

- No Match
  - If none of the K distributions match the current pixel value, the least probable distribution is go out.
  - A new distribution with the current value as its mean value, an initially high variance, and low prior weight, is enter .
  - The mean and variance remain unchanged.

Background Model Estimation

- Gaussians are ordered by the value (ω/σ
- We are interested in the Gaussian distributions which have the most **<u>supporting evidence</u>** = and the **<u>least variance</u>**. Why??

- For "background" distributions when a static, persistent object is visible, leading to high weight and relatively low variance.

- New object occludes the background object creation of a distribution or the increase in the variance of an existing distribution, so the variance of the moving object is expected to remain larger than a background pixel until the moving object stops

Background Estimation Example

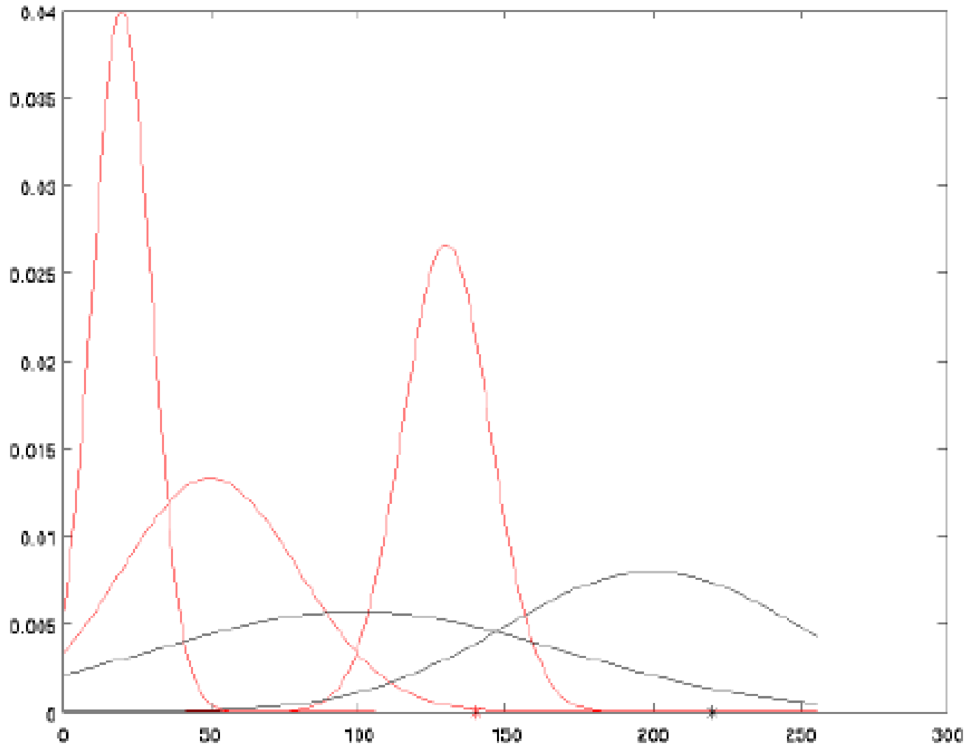
- First B distributions are selected as the background

$$B = argmin_b(\sum_{i=1}^{b} w_i > T)$$

- As we remember, W_i is portion of data that is accounted for by i Gaussian
- T minimum portion of image expected to be background

Background Estimation Example

- After background estimation red are backgrounds and blacks are foreground



Discussion

- Advantageous
  - Different threshold for each pixel
  - Pixel-wise thresholds adapt over time
  - Objects are allowed to become part of the background without destroying the existing background model
  - Provides fast recovery
- Disadvantages
  - Can not handle sudden, drastic lighting changes
  - Must have good Gaussian initialization (median filtering)
  - There are number of parameters to tune

Summary

- Simple background subtraction approaches such as fame diff, mean, and median filtering are fast
- Constant thresholds make them ill-suited for challenging real-world problems
- Adaptive background mixture model approach can handle challenging situations
- Bimodal backgrounds, long-term scene changes, and repetitive motion
- Improvements include upgrade the approach with temporal information or using region-based techniques

Thank You

- Questions?