Motion Detection and Tracking

CS6350: Computer Vision

Indian Institute of Technology, Madras

Visualization and Perception Lab

Presentation Outline

- Introduction to Motion Detection
- Applications of Motion Detection and Tracking
- Background Subtraction (BGS)
- Basic BGS Algorithms
- Mixture of Gaussians (MoG)
- Conclusion

Introduction

- **AIM:** To detect and track objects moving independently to the background

- Two situations encountered are
  - Static Camera (fixed viewpoint)
  - Moving Camera (moving viewpoint) (research topic, out of scope, left for exploration)

Definition of Motion Detection

- Action of sensing physical movement in a given area

- Motion can be detected by measuring change in speed or vector of an object

Applications of Motion Detection and Tracking

- Surveillance/Monitoring Applications
  - Security Cameras
  - Traffic Monitoring
  - People Counting
- Control Applications
  - Object Avoidance
  - Automatic Guidance
  - Head Tracking for Video Conferencing

Many intelligent video analysis systems are based on motion detection and tracking

Detecting moving objects in a static scene

- Moving objects can be detected by applying Background Subtraction Algorithms
- Simplest method (frame differencing):
  - Subtract consecutive frames
  - Ideally this will leave only moving objects
  - Following conditions effect the background subtraction
    - Moving background (e.g. swaying of trees)
    - Temporarily stationary objects
    - Object shadows
    - Illumination variation

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Background Subtraction

- **Motivation:** Simple difference (frame differencing) of two images shows moving objects
- Uses a reference background image for comparison purposes
- Current image (containing target object) is compared to reference image pixel by pixel
- Places where there are differences are detected and classified as moving objects

Overview of Various BGS Algorithms

BGS Algorithm	Reference Paper	Salient Features
Adaptive Median Filtering (AMF) (Running Average)	*N. McFarlane and C. Schofield, “Segmentation and Tracking of Piglets in Images”, Machine Vision and Applications, Vol. 8, No. 3. (1 May 1995*), pp. 187-193	• Background pixel is modeled as weighted average where recent frames have higher weight • Parametric thus less memory intensive
Running Gaussian Average	"Pfinder: real-time tracking of the human body" by C. Wren et al *Automatic Face and Gesture Recognition, 1996., Proceedings of the Second International Conference on* , vol., no., pp.51-56, 14-16 Oct 1996	• Pfinder adopts a Maximum A Posteriori Probability (MAP) approach. • It first models the person, then the scene and then does analysis
Mixture of Gaussians (MoG) (Stauffer and Grimson method)	Stauffer, C.; Grimson, W.E.L. , "Learning patterns of activity using real-time tracking”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.22, no.8, pp.747-757, Aug 2000	• Each pixel is a mixture of Gaussians. • Gaussians modify and adapt with each new incoming frame

Overview of Various BGS Algorithms (contd..)

BGS Algorithm	Reference Paper	Salient Features
Zivkovic AGMM (adaptive Gaussian mixture models)	Zivkovic, Z.; "Improved adaptive Gaussian mixture model for background subtraction", Pattern Recognition, 2004, Proceedings of the 17th International Conference on ICPR 2004, vol.2, no., pp. 28-31 Vol.2, 23-26 Aug. 2004	• Uses Gaussian mixture probability density • The Gaussian mixture parameters and components of each pixel is updated online
Eigenbackgrounds	Oliver, N.M.; Rosario, B.; Pentland, A.P.; "A Bayesian computer vision system for modeling human interactions", IEEE Transactions on Pattern Analysis and Machine Intelligence , vol.22, no.8, pp.831-843, Aug 2000	• PCA by way of eigenvector decomposiion is a way to reduce the dimensionality of a space • PCA can be applied to a sequence of n frames to compute the eigenbackgrounds • Faster than MoG approach
Prati Mediod (mediod filtering)	Cucchiara, R.; Grana, C.; Piccardi, M.; Prati, A.; "Detecting moving objects, ghosts, and shadows in video streams," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.25, no.10, pp. 1337- 1342, Oct. 2003	• Pixels of moving objects, shadows etc., are processed differently • Uses Median function

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Basic BGS Algorithms

- Background as the **average** or the **median** (Velastin, 2000; Cucchiara, 2003) of the previous *n* frames:
  - rather fast, but very memory consuming: the memory requirement is *n* * size(frame)
- Background as the Approximate Median Filtering (AMF) (**running average**)

$$B_{i+1} = \alpha * I_i + (1 - \alpha) * B_i$$

  - α, the learning rate, is typically 0.05
  - no more memory requirements

Basic BGS Algorithms – rationale

- The background model at each pixel location **is based on the pixel's recent history**
- In many works, such history is:
  - just the previous *n* frames
  - a weighted average where recent frames have higher weight
- In essence, the background model is computed as a chronological average from the pixel's history
- No spatial correlation is used between different (neighbouring) pixel locations

Results - Simple frame differencing

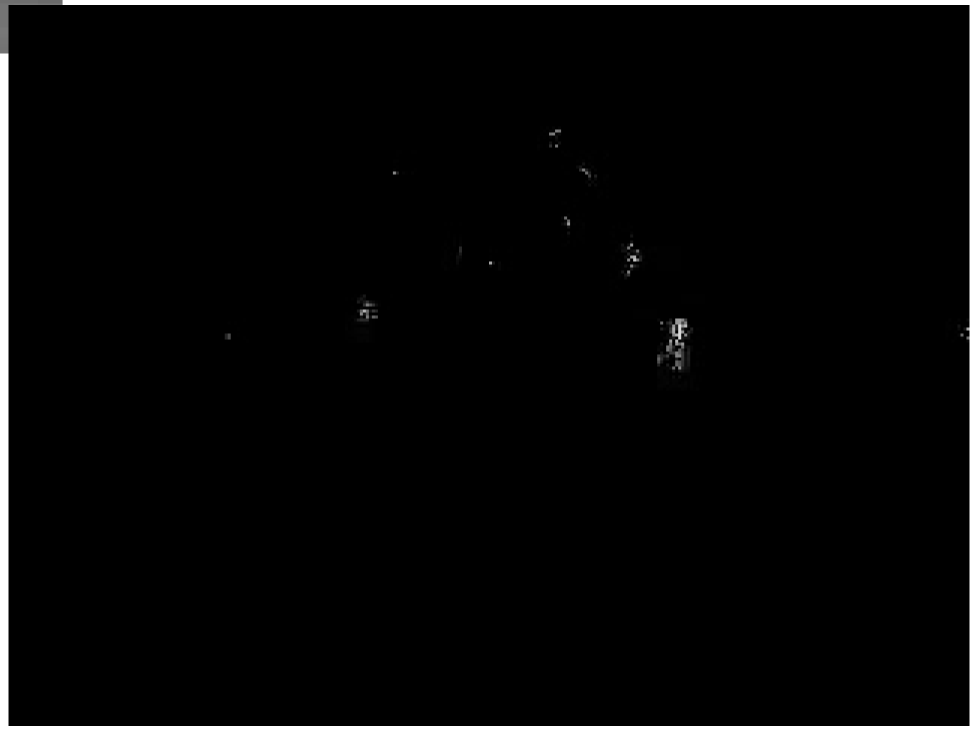
INPUT Video

Foreground Mask

Results - Approximate Median Filtering

Background Model

Foreground Mask



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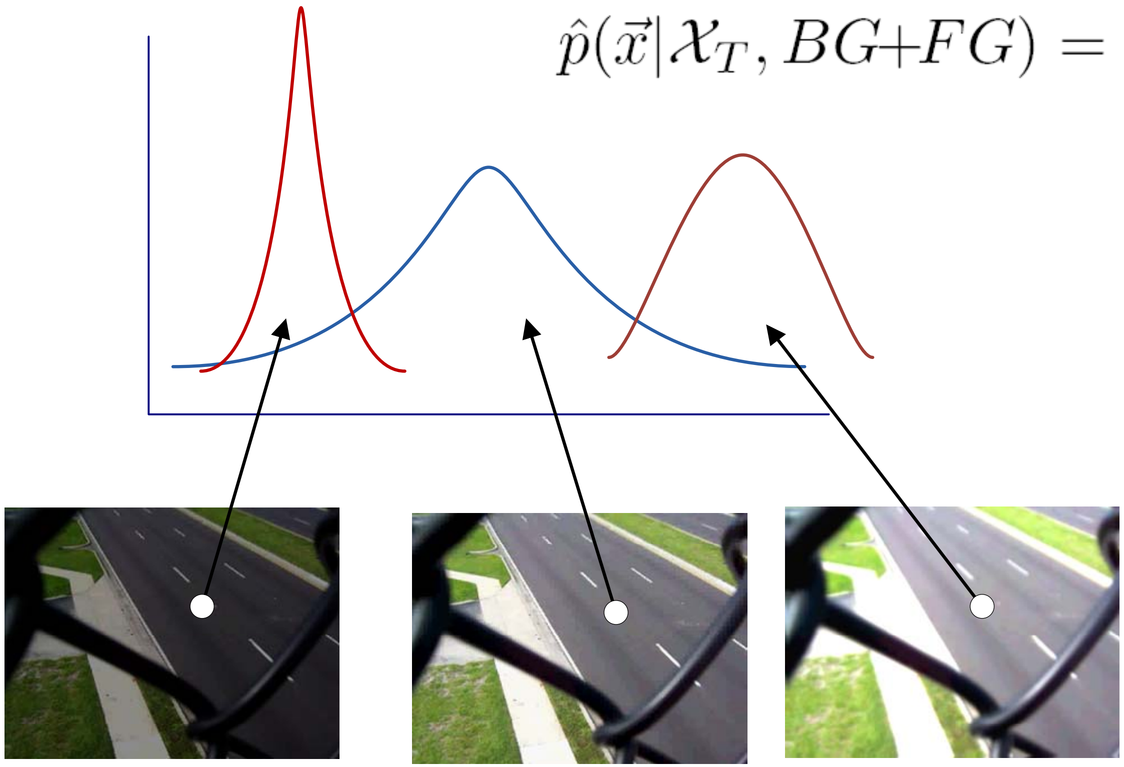
Mixture of Gaussians (MoG)

- Mixture of *K* Gaussians (μ_i, σ_i, ω_i)(Stauffer and Grimson, 2000)
- In this way, the model copes also with multimodal background distributions; however:
  - the number of modes is arbitrarily pre-defined (usually from 3 to 5)
  - how to initialize the Gaussians?
  - how to update them over time?

Gaussian Mixture Models

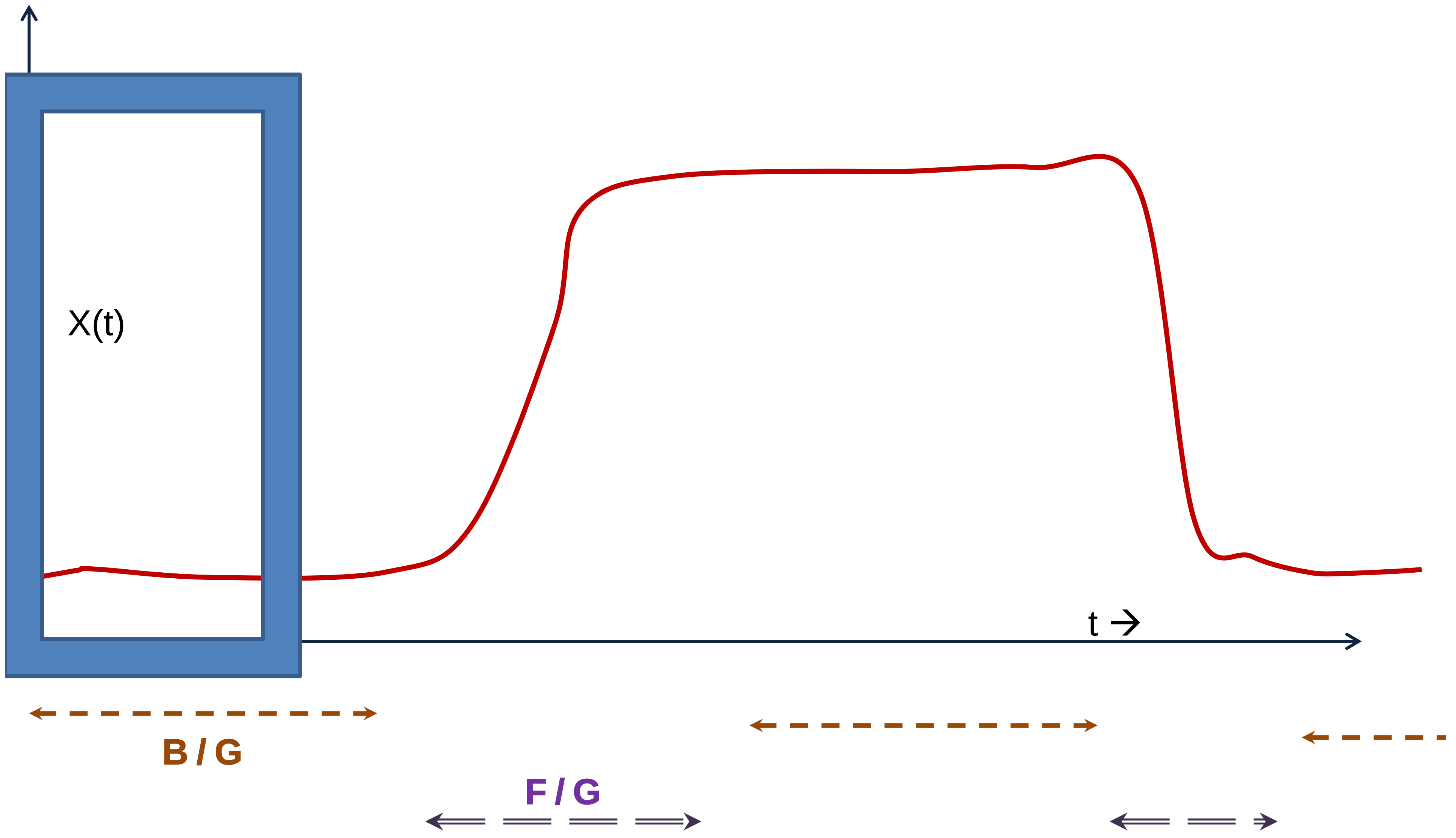
- Each pixel modeled with a mixture of Gaussians
- Flexible to handle variations in the background

$$\hat{p}(\vec{x}|\mathcal{X}_T, BG{+}FG) = \sum_{m=1}^{M} \hat{\pi}_m \mathcal{N}(\vec{x}; \widehat{\vec{\mu}}_m, \widehat{\sigma}_m^2 I)$$



Mixture of Gaussians (MoG) (contd.)

- All weights ω_i are updated (updated and/or normalized) at every new frame
- At every new frame, some of the Gaussians "match" the current value (those at a distance < 2.5 σ_i): for them, μ_i , σ_i are updated by the running average
- The mixture of Gaussians actually models both the foreground and the background: how to pick only the distributions modeling the background?:
  - all distributions are ranked according to their ω_i/σ_i and the first ones chosen as "background"


X(t)
t →
B / G
F / G

GMM Background Subtraction

- Two tasks performed real-time
  - Learning the background model
  - Classifying pixels as background or foreground

- Learning the background model
  - The parameters of Gaussians
    - Mean
    - Variance and
    - Weight
  - Number of Gaussians per pixel

- Enhanced GMM is 20% faster than the original GMM*

* Improved Adaptive Gaussian Mixture Model for Background Subtraction , Zoran Zivkovic, ICPR 2004

Classifying Pixels

- $\vec{x}^{(t)}$ = value of a pixel at time t in RGB color space.
- Bayesian decision R – if pixel is background (BG) or foreground (FG):

$$R = \frac{p(BG|\vec{x}^{(t)})}{p(FG|\vec{x}^{(t)})} = \frac{p(\vec{x}^{(t)}|BG)p(BG)}{p(\vec{x}^{(t)}|FG)p(FG)}$$

- Initially set p(FG) = p(BG), therefore if $p(\vec{x}^{(t)}|BG) > c_{thr}$ decide background

$$p(\vec{x}^{(t)}|FG) = c_{FG}$$

$p(\vec{x}^{(t)}|BG)$ = Background Model

$\hat{p}(\vec{x}|\mathcal{X}, BG)$ = Estimated model, based on the training set X

The GMM Model

- Choose a reasonable time period T and at time t we have
  $\mathcal{X}_T = \{x^{(t)}, ..., x^{(t-T)}\}$
- For each new sample update the training data set $\mathcal{X}_T$
- Re-estimate $\hat{p}(\vec{x}|\mathcal{X}_T, BG)$
- Full scene model (BG + FG)

$$\hat{p}(\vec{x}|\mathcal{X}_T, BG{+}FG) = \sum_{m=1}^{M} \hat{\pi}_m \mathcal{N}(\vec{x}; \widehat{\vec{\mu}}_m, \widehat{\sigma}_m^2 I)$$

GMM with M Gaussians where

- $\widehat{\vec{\mu}}_1, ..., \widehat{\vec{\mu}}_M$ - estimates of the means
- $\widehat{\sigma}_1, ..., \widehat{\sigma}_M$ - estimates of the variances
- $\hat{\pi}_m$ - mixing weights non-negative and add up to one.

The Update Equations

- Given a new data sample $\vec{x}^{(t)}$ update equations

$$\hat{\pi}_m \leftarrow \hat{\pi}_m + \alpha(o_m^{(t)} - \hat{\pi}_m)$$
$$\widehat{\vec{\mu}}_m \leftarrow \widehat{\vec{\mu}}_m + o_m^{(t)}(\alpha/\hat{\pi}_m)\vec{\delta}_m$$
$$\widehat{\sigma}_m^2 \leftarrow \widehat{\sigma}_m^2 + o_m^{(t)}(\alpha/\hat{\pi}_m)(\vec{\delta}_m^T\vec{\delta}_m - \widehat{\sigma}_m^2)$$

where, $\vec{\delta}_m = \vec{x}^{(t)} - \widehat{\vec{\mu}}_m$

$o_m^{(t)}$ is set to 1 for the 'close' Gaussian and 0 for others

and $\alpha = 1/T$ is used to limit the influence of old data (learning rate).

- An on-line clustering algorithm.
- Discarding the Gaussians with small weights - approximate the background model :

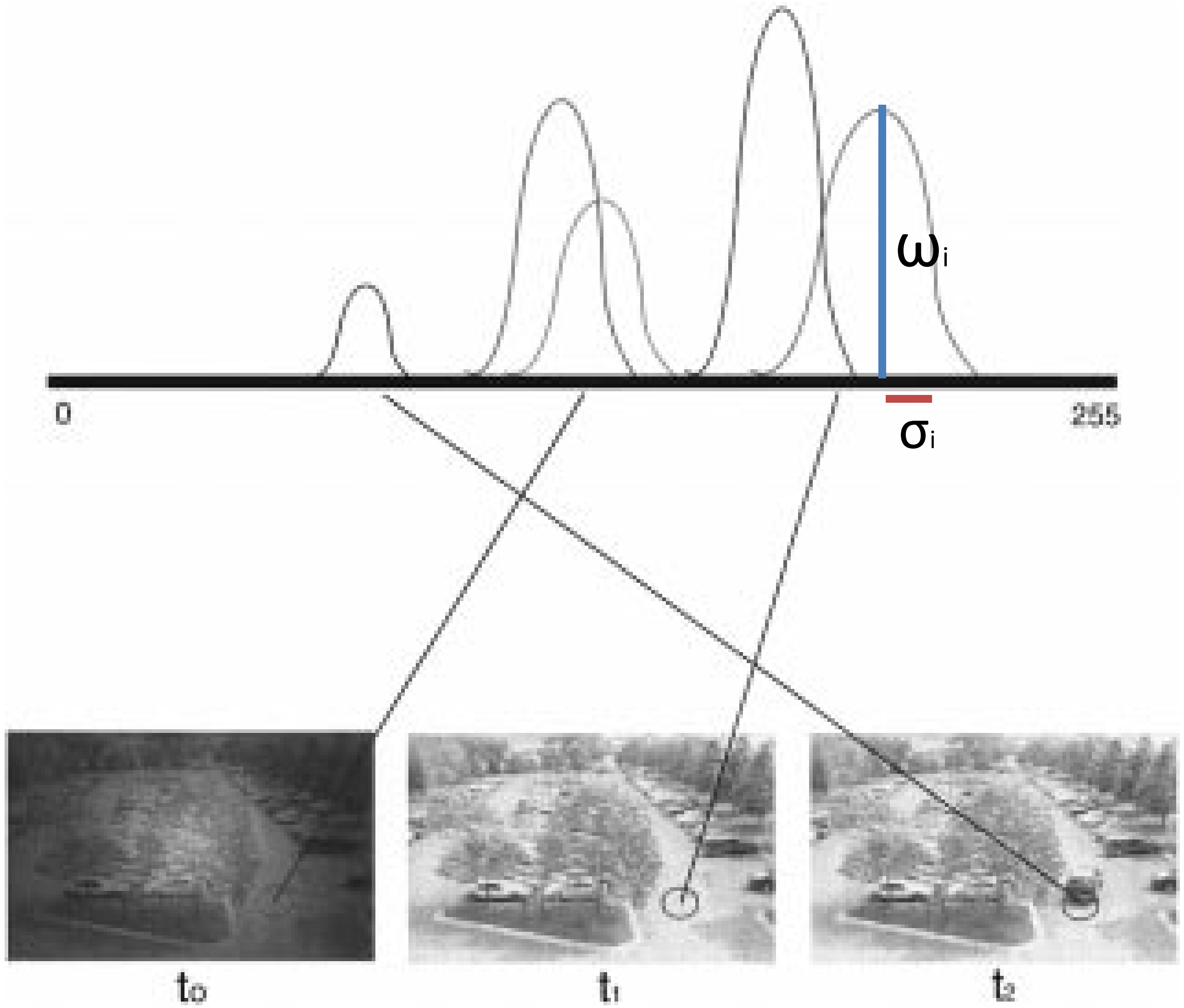
$$p(\vec{x}|\mathcal{X}_T, BG) \sim \sum_{m=1}^{B} \hat{\pi}_m \mathcal{N}(\vec{x}; \widehat{\vec{\mu}}_m, \sigma_m^2 I)$$

- If the Gaussians are sorted to have descending weights $\hat{\pi}_m$

$$B = \arg\min_b \left(\sum_{m=1}^{b} \hat{\pi}_m > (1 - c_f) \right)$$

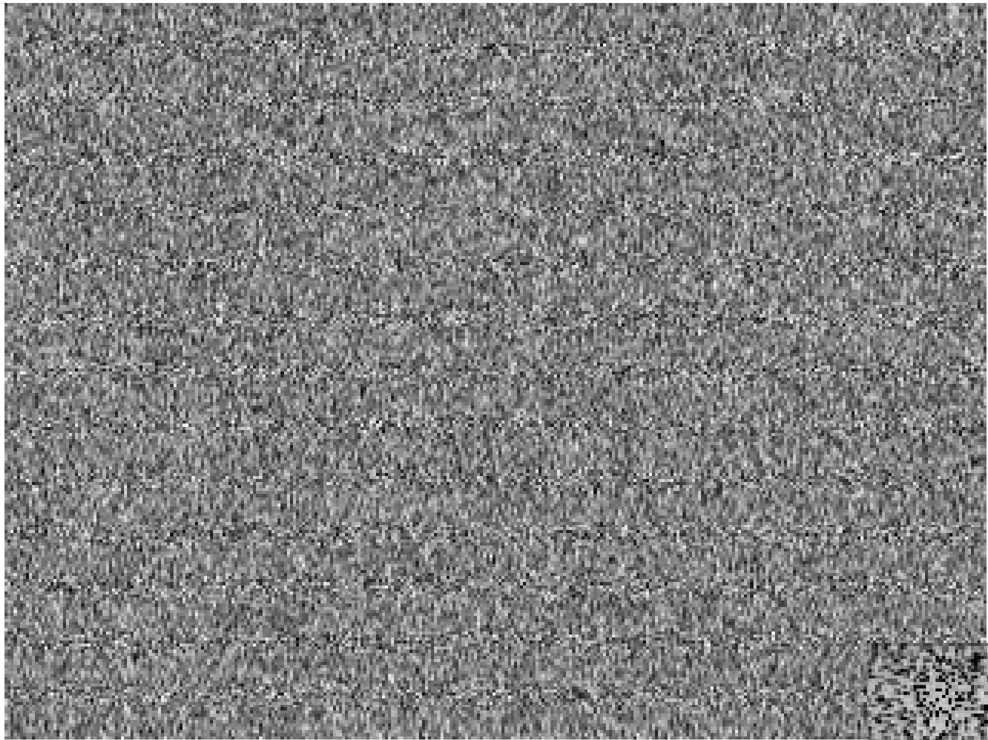
where c_f is a measure of the maximum portion of data that can belong to FG without influencing the BG model

Mixture of Gaussians (MoG) (contd.)



From:- I. Pavlidis, V. Morellas, P. Tsiamyrtzis, and S. Harp, "Urban Surveillance Systems: From the Laboratory to the Commercial World". IEEE Proceedings, 89(10), pp. 1478-1497, Oct., 2001.

Results - Mixture of Gaussians (MoG)



Background Model

Foreground Mask

Conclusion

- Studied various motion detection and tracking algorithms
- Multiple BGS methods are needed for
  - Indoor (relative stable lighting)
  - Outdoor
    - Relative stable
    - High dynamic
  - Crowded environment
  - Camera Jitter/Shaking

Conclusion (contd.)

- Speed
  - Fast
    - Average, Median, Approximate median filtering
  - Intermediate
    - Eigenbackgrounds
  - Slow
    - MoG
- Memory requirements
  - High
    - Average, Median
  - Intermediate
    - MoG, Eigenbackgrounds
  - Low
    - Approximate median filtering