

Motion Detection and Tracking

CS6350: Computer Vision



Indian Institute of
Technology, Madras



Visualization and
Perception Lab

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

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)	<i>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</i>	<ul style="list-style-type: none"> Background pixel is modeled as weighted average where recent frames have higher weight Parametric thus less memory intensive
Running Gaussian Average	<i>"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</i>	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • PCA by way of eigenvector decomposition 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	<ul style="list-style-type: none"> • Pixels of moving objects, shadows etc., are processed differently • Uses Median function

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 $n * \text{size}(\text{frame})$
- 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



INPUT Video

Results - Simple frame differencing



**Foreground
Mask**

Results - Approximate Median Filtering



**Background
Model**

**Foreground
Mask**



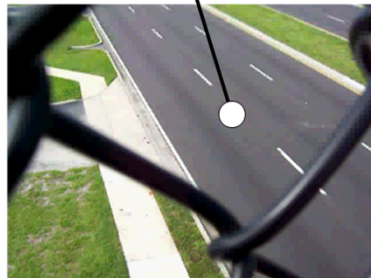
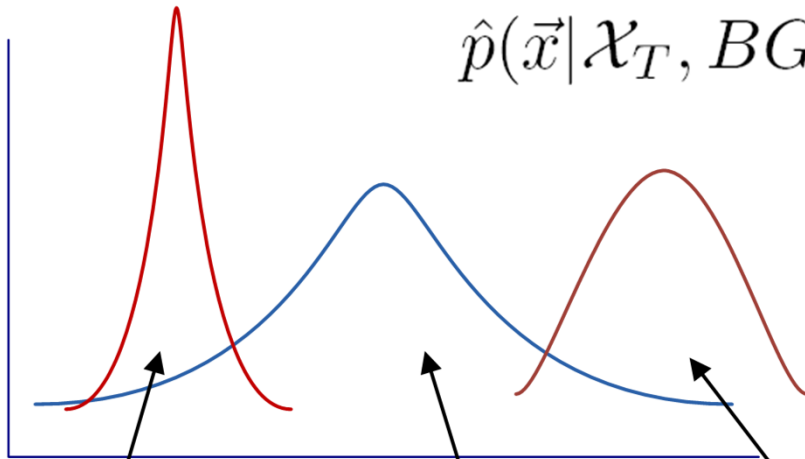
Mixture of Gaussians (MoG)

- Mixture of K Gaussians ($\mu_i, \sigma_i, \omega_i$)(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

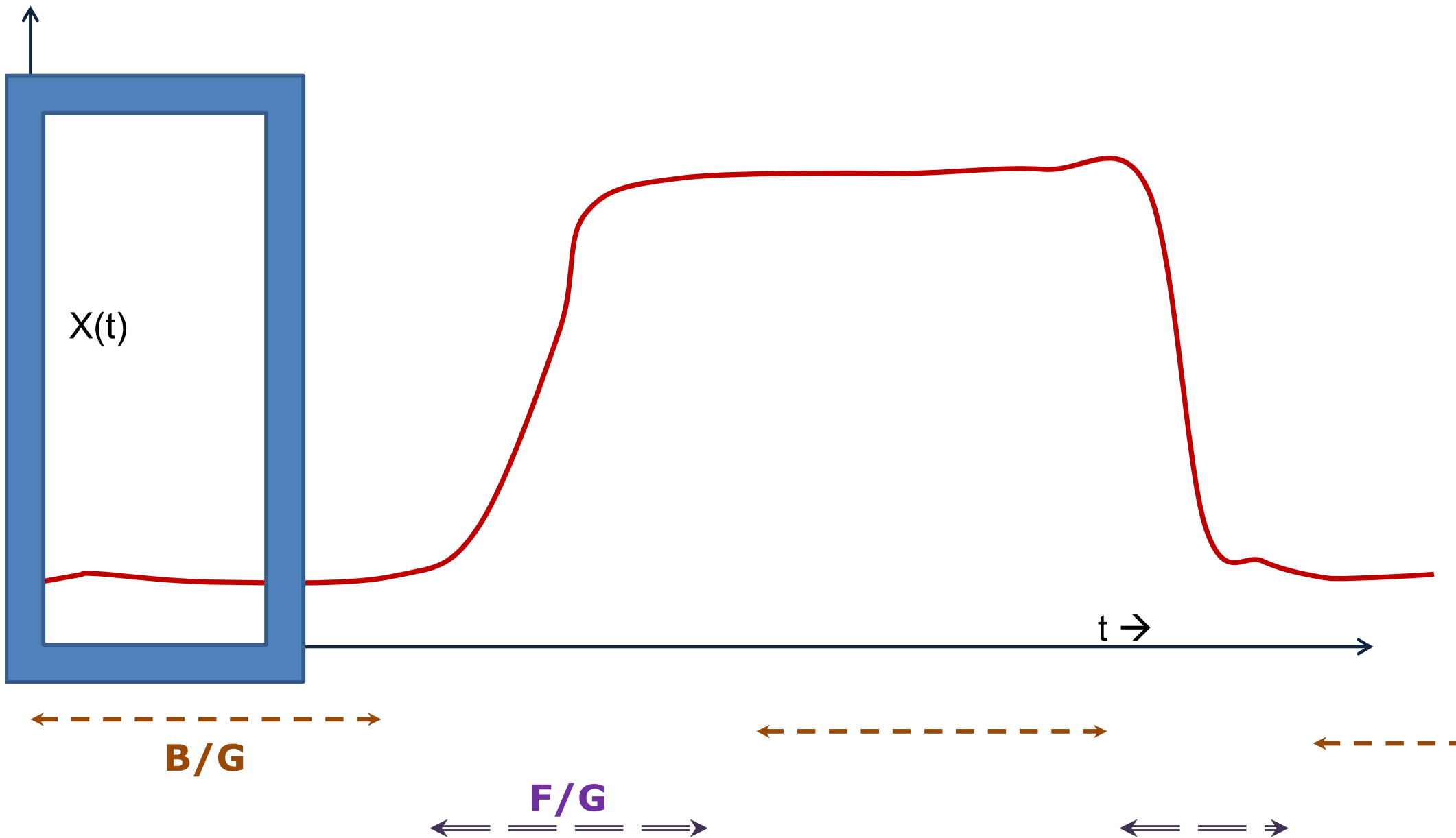
- Each pixel modeled with a mixture of Gaussians
- Flexible to handle variations in the background

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



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 $< 2.5 \sigma_i$): 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”



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

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

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

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

The GMM Model

- Choose a reasonable time period T and at time t we have

$$\mathcal{X}_T = \{x^{(t)}, \dots, x^{(t-T)}\}$$

- 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)

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

GMM with M Gaussians where

- $\hat{\vec{\mu}}_1, \dots, \hat{\vec{\mu}}_M$ - estimates of the means
- $\hat{\sigma}_1, \dots, \hat{\sigma}_M$ - 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

$$\hat{\pi}_m \leftarrow \hat{\pi}_m + \alpha(o_m^{(t)} - \hat{\pi}_m)$$

$$\hat{\vec{\mu}}_m \leftarrow \hat{\vec{\mu}}_m + o_m^{(t)}(\alpha/\hat{\pi}_m)\vec{\delta}_m$$

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

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

$o_m^{(t)}$ 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 :

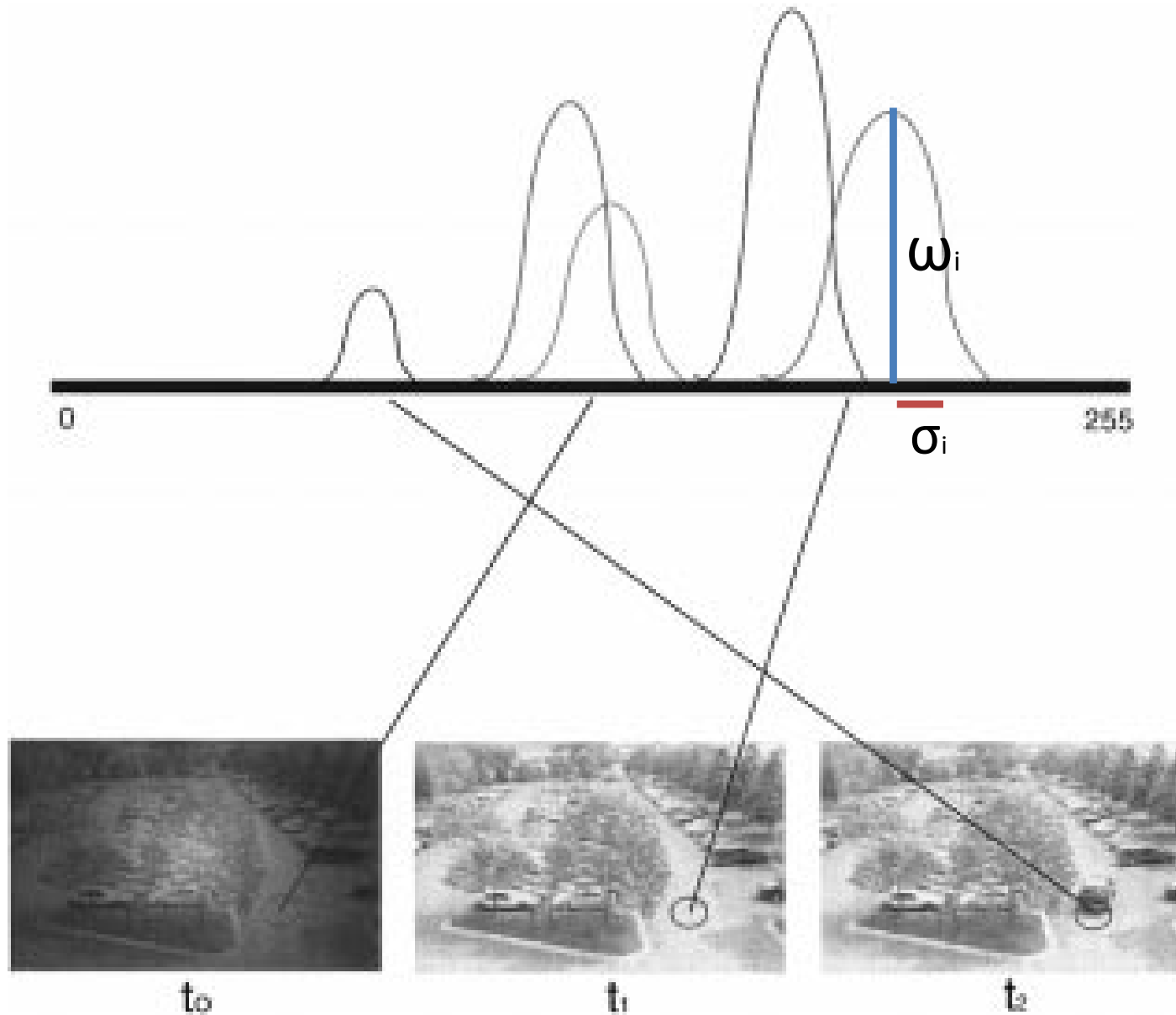
$$p(\vec{x}|\mathcal{X}_T, BG) \sim \sum_{m=1}^B \hat{\pi}_m \mathcal{N}(\vec{x}; \hat{\vec{\mu}}_m, \sigma_m^2 I)$$

- 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. Tsiamyrztis, 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





AMF



MOG



ED

But if camera moves?



Desired →



STAR: A Content Based Video Retrieval Framework
for Moving Camera Video Shots

CVPR'13



ICCV'13



PAMI'14



BMVC'14

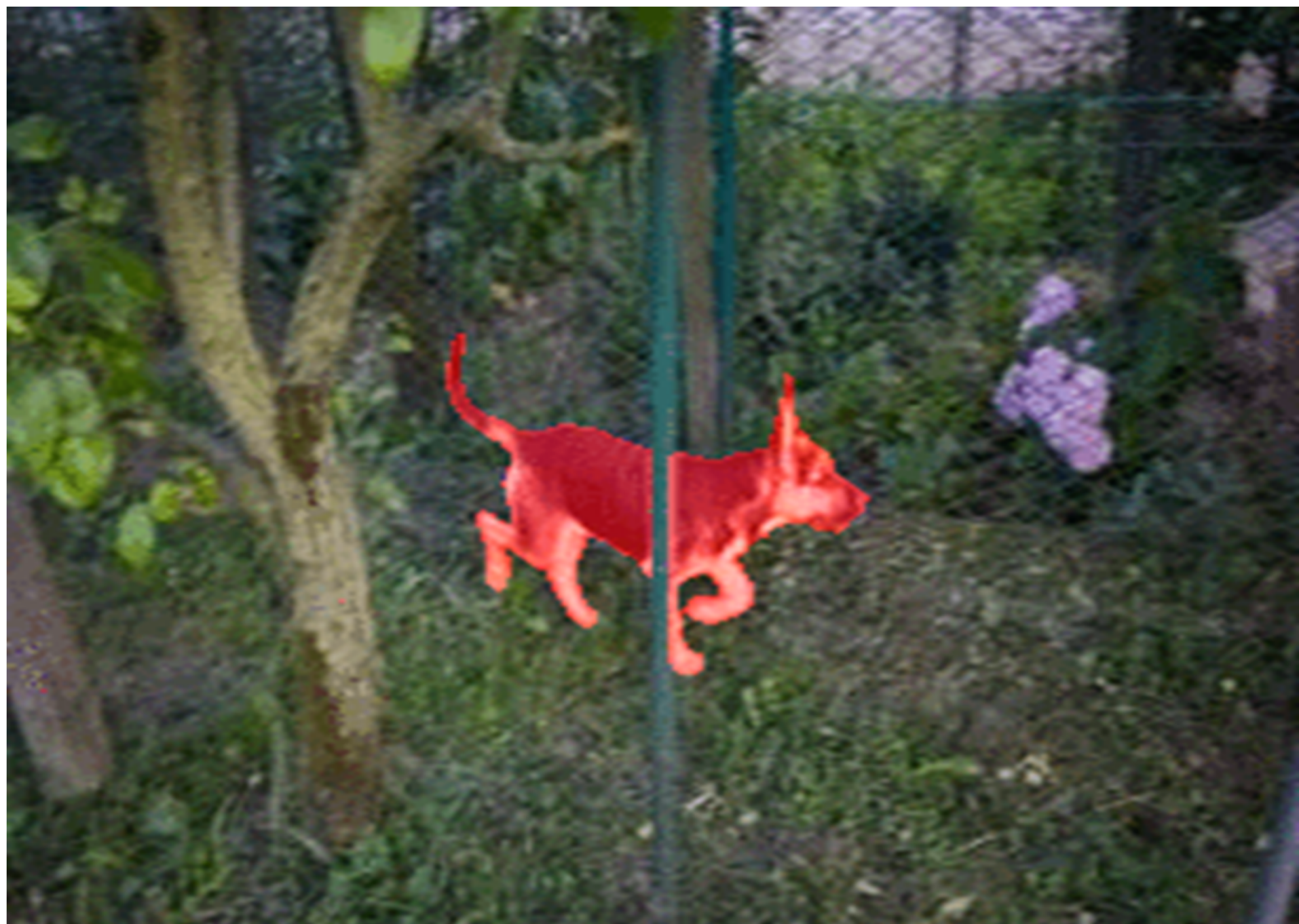


CVPR'15



OURS





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



