1 Statistical Signal Modelling

1.2: Modelling of memoryless sources

1.2.c: Video Example

Statistical Signal Modelling

1.2

1. Introduction to IPA and Random variable
2. **Modelling of memoryless processes**
    - Sample-wise operators
    - Uniform and non-uniform quantization
    - Examples: Sample-wise video processing
3. **Discrete Stochastic Processes**
    - Definition
    - Autocorrelation: Deterministic signals and processes
    - Stationarity and Ergodicity
    - Power Spectral Density (PSD)
    - Stochastic processes filtering
    - Examples

Unit Structure

1.2

1. Introduction
2. Still background estimation
3. Variable background estimation: Single Gaussian
4. Variable background estimation: Multiple Gaussians
5. Conclusions

Introduction

1.2

- Many **security applications** require to prompt an alarm to **trigger a recorder** or to allow a **human operator** to evaluate the situation:
  - Control of large areas with a large number of cameras/screens to be monitored
  - False positive are accepted to avoid overlooking a potential danger

- To detect the presence of a person/object, it is not necessary to get its shape or trajectory
- The method can rely on a **sample-based model of the image**:
  - Compute the pixel to pixel difference between images.

Still background estimation

1.2

- In several security applications, due to **the setting** and **camera configuration**, the change detection can be understood as a problem of **still background estimation**.



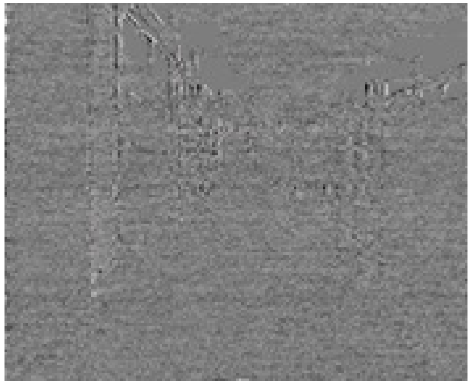
- A **static camera** is observing a scene that, in principle**,** does not vary: **background**.
- A **large variation** can be detected by comparison with the background: **foreground object/person.**

Still background modelling

1.2

- A **static camera** is observing a scene that, **in principle**, does not vary: **background**.

Magnified difference image

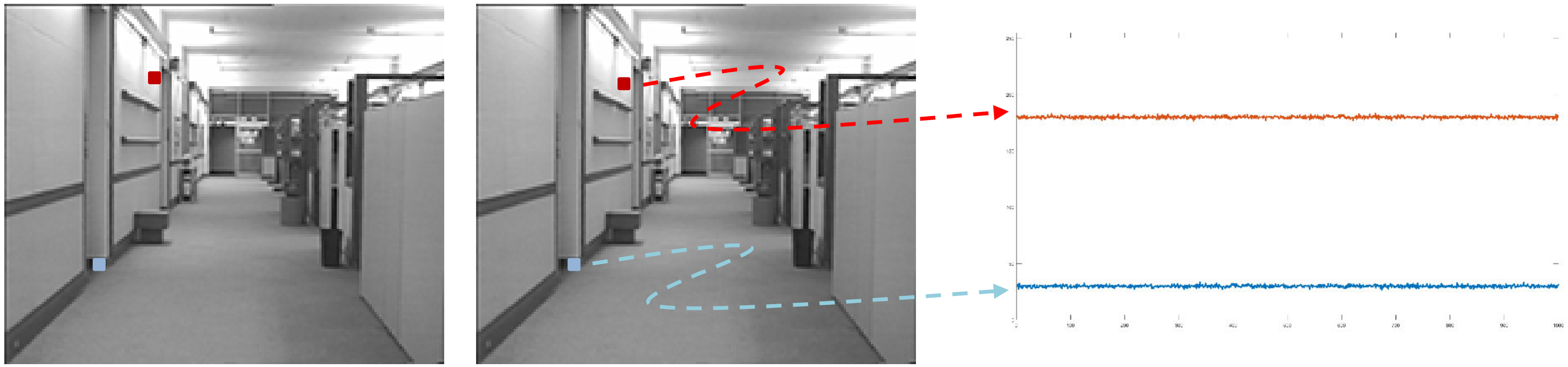


- Every pixel of the **background** is modeled as a **random variable**:
  - The **mean** (μ_p) represents the pixel actual value
  - The **variation** with respect to the mean is (mainly) due to the noise introduced by the camera.

Still background modelling

Every pixel of the **background** is modeled as a **random variable**:

- Camera pixels are usually assumed to be **independent** and **similar**. Therefore, the noise variables (pixels) are modeled as independent and identical distributed (iid) random variables.
- The noise probability distribution of each pixel is often modeled as **Gaussian** $N\left(0, \sigma_p^2\right)$ or the empirical distribution is used.
- The noise image is model as a **stationary, white, zero-mean** process.



Foreground modelling

1.2

Every pixel of the **foreground** is modeled as a **random variable**:

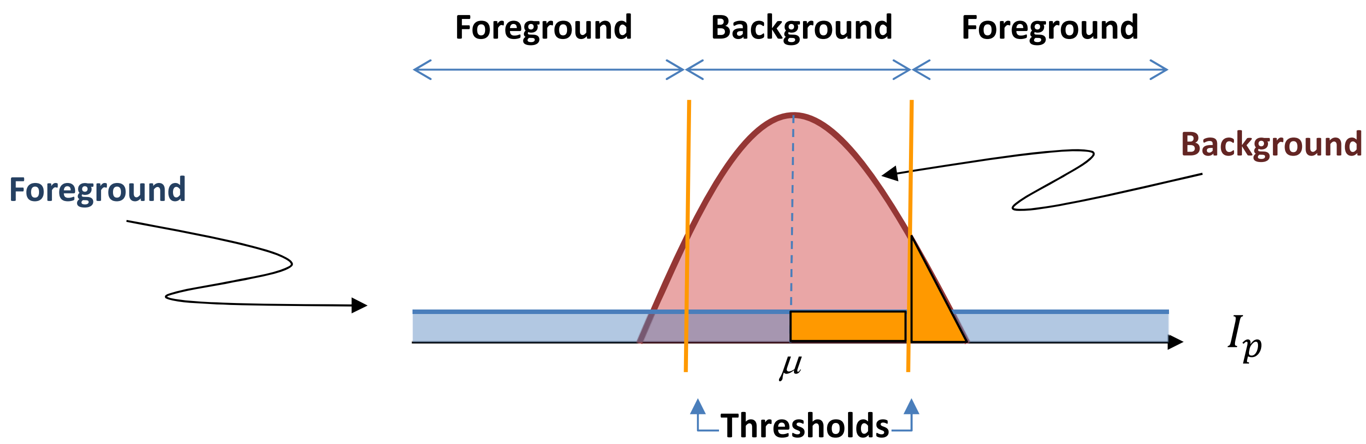
- **No a priori information** can be assumed on foreground elements.
- The **source of information** can be related to intruders or even to artifacts produced in the recording of the scene.
  - A **uniformly distributed probability function** is commonly assumed

Foreground / Background decision

1.2

- Once background and foreground have been statistically modeled, changes in the scene are detected by a **classification procedure**.
- A **Maximum Likelihood** classifier is commonly used. It minimizes the probability of error in the classification.
- Every pixel (p) in a new image (I) is **separately analyzed**. If the pixel value falls in-between the two thresholds, the pixel is classified as background.

Pixel pdf



Example of still background estimation

1.2

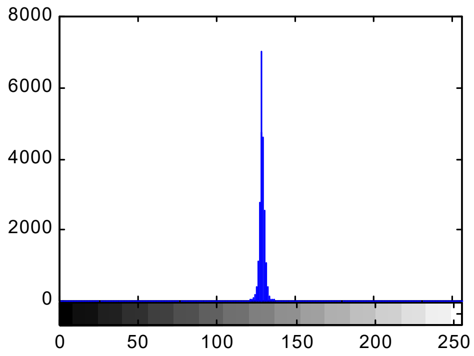
Various realizations of the background are necessary to estimate the mean of each background pixel model. **How do we compute it?**

Realizations of the *Background* process

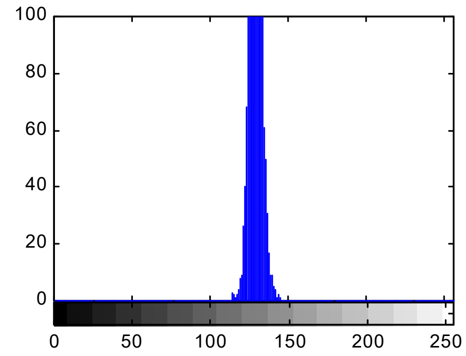
Example of still background estimation

1.2

The **histograms of background pixels** give an estimate of the probability density functions of the noise.



Histogram



Zoom of the histogram

Thresholds are fixed for each pixel: for example here 108 and 148 (mean ± 20).

Is that the best way to classify the pixels (binarize the image)?

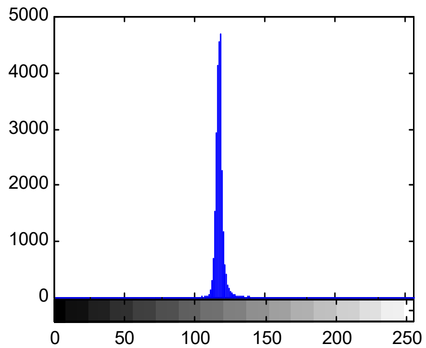
Example of still background estimation

1.2

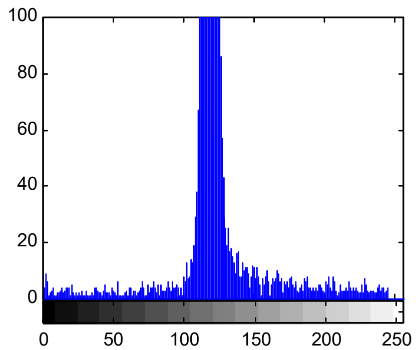
Background image

Input image

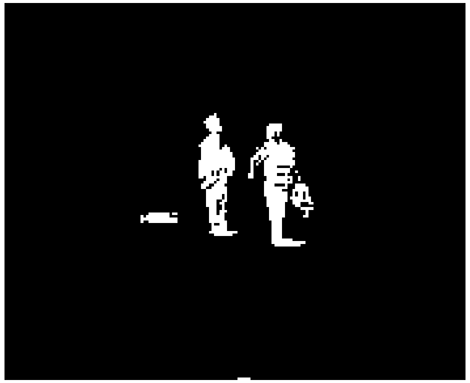
Difference image



Pixel Histogram



Zoom of the histogram



Change detection result.
Thresholds: mean ± 20

Example of still background estimation

1.2

Segment of the original sequence
Hall Monitor

Example of still background estimation

1.2

Change detection on *Hall Monitor*

Further problems

1.2

- When large areas have to be monitored, **cameras may not be static** but may scan a given area:

✓ Images are compared against a **panoramic view of the scene**. The system has to know where the camera is pointing to at every instant.

- The **variations in the background pixel values** can be larger than expected because of:
  - **Changes in the illumination** of the scene
  - **Exterior scenes**: typically, this leads to non-static backgrounds.

  ✓ Techniques for **variable background estimation** are used.

Unit Structure

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Variable background estimation

1.2

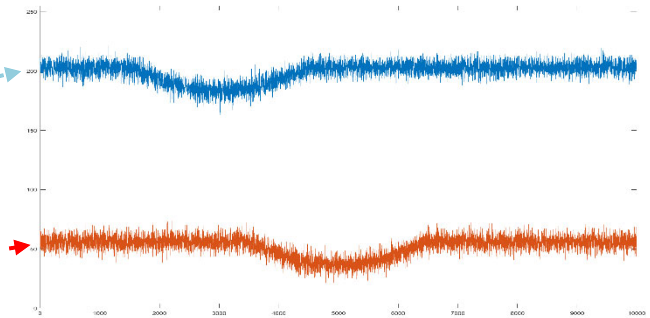
- In several security applications, due to **the setting** and **camera configuration**, the change detection can be understood as a problem of **variable background estimation**.

- A static camera is observing a scene (**background**) that may **slowly vary** (day light changes, clouds, etc).
- In addition, smaller variations appear due to camera sensor noise.

Variable background estimation

1.2

- The **background model** has to account for those possible slow variations.



- Every pixel of the **background** is modeled as a **random variable**:
  - Its mean may **slowly change** through time ($\mu_p[n]$)

$$\mu_p[n] = (1-\rho)\mu_p[n-1] + \rho I_p[n]$$

Variable background estimation

1.2

- Every pixel of the **background** is modeled as a **random variable**:
  - Its mean may **slowly change** through time ($\mu_p[n]$)

$$\mu_p[n] = (1-\rho)\mu_p[n-1] + \rho I_p[n]$$

  - As before, in the absence of foreground objects, **variations with respect to the mean** are due to the noise introduced by the camera.
    - Noise samples are assumed to be **independent** and **identically distributed**. IID modeled as **Gaussian** $N\left(0, \sigma_p^2\right)$ functions.
    - Its variance might be re-estimated through time $\left(\sigma_p^2[n]\right)$.

$$\sigma_p^2[n] = (1-\rho)\sigma_p^2[n-1] + \rho\left(I_p[n] - \mu_p[n]\right)^2$$

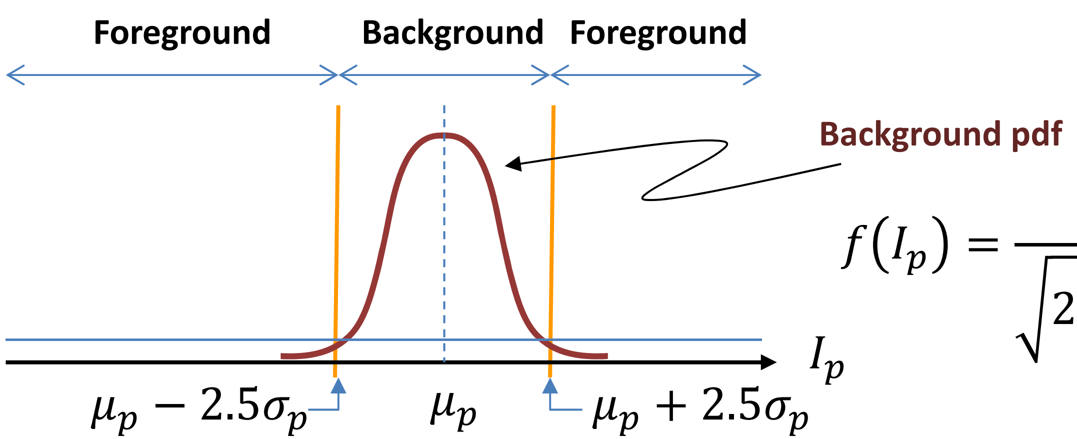
Should we always update the background model parameters?

Variable background classification

1.2

- Every pixel of the **foreground** is modeled as a **random variable**:
  - **No a priori information** can be assumed on foreground elements.
  - A **uniformly distributed probability function** is assumed.

- Once background and foreground have been modeled, changes in the scene can be detected by a **classification process**. In a given instant (n):



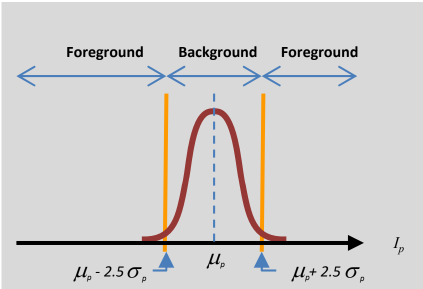
$$f(I_p) = \frac{1}{\sqrt{2\pi\sigma_p^2}} \exp\left(-\frac{(I_p - \mu_p)^2}{2\sigma_p^2}\right)$$

Variable background classification

1.2

The process is divided into two steps:

- **Initialization**: During a training period, the initial **mean** and **variance** values of all Gaussian variables (μ_p, σ_p) are estimated.
- **Update**: The mean and variance of Gaussian variables are updated if the **incoming pixels are classified as background**.

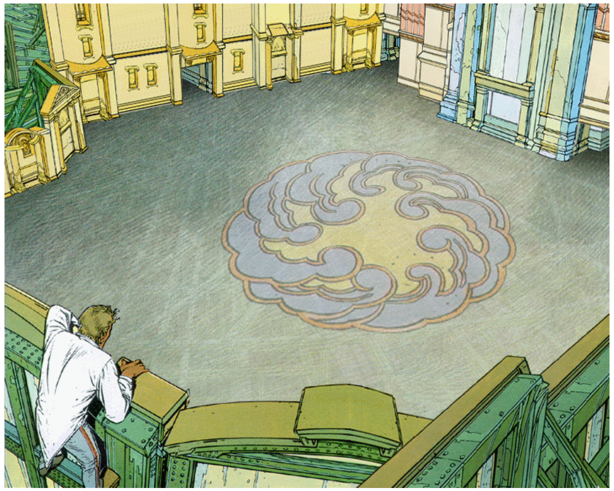


$$\mu_p[n] = \begin{cases} (1-\rho)\mu_p[n-1] + \rho I_p[n] & \text{if } p \in B \\ \mu_p[n-1] & \text{if } p \in F \end{cases}$$

$$\sigma_p^2[n] = \begin{cases} (1-\rho)\sigma_p^2[n-1] + \rho\left(I_p[n] - \mu_p[n]\right)^2 & \text{if } p \in B \\ \sigma_p^2[n-1] & \text{if } p \in F \end{cases}$$

- The parameter ρ establishes the **memory of the system**:
  - $\rho \approx 0$ implies no updating (**long memory**)

Variable background classification



Urbicande-La-Neuve (UCL – Alterface)

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Variable background estimation (MG)

1.2

- In several security applications, systems have to model **large variability of the background** due to switch between **various states of the background**

White?
Green?
Black?

Variable background estimation (MG)

1.2

- Moreover, **new objects** that remain in the scene for a long period have to **be assimilated to the background.**

Variable background estimation (MG)

1.2

What will the system output for the following sequence?

Variable background estimation (MG)

1.2

What should the system output be for the following sequence?

Unit Structure

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