Detection of Uncovered Background & Moving Pixels

Presented By,
Jignesh Panchal

Overview

- Introduction of the Problem
- Formulation of binary hypothesis
  - Mathematical formulations
  - Formulation of Likelihood Ratio Test
  - Evaluation of LRT
- Analysis using noisy images (Gaussian White Noise)
- Extension of binary hypothesis to 3-ary hypothesis
- Performance analysis
- Conclusion and future work

Introduction

- There is a very high demand for the video signal communication services. This requires a tremendous quantity of digital data transmission.
- Motion-Compensated interframe coding is the most effective method for reducing the quantity of transmitted information. (redundancy)
- Degradation occurs, as these schemes do not provide uncovered background pixels.
- Good coding scheme will use background prediction in addition to motion compensation for interframe coding.
- Detection based on Change Detection: but sensitive to Noise.

Introduction (Contd.)

- The basis of my method is hypothesis testing using Bayes decision criterion.
- This method directly considers image noise and is thus more robust than change detection.
- In this method, computationally expensive motion estimation is not required for segmentation.
- The detection of uncovered background and moving pixels in image sequences is an essential part of uncovered background prediction and motion compensation for sequence coding.

Mathematical Formulation

- Consider two consecutive image frames in a sequence of image frames, and write the noisy intensities of the first image frame as:

$$z_1(k) = s\,(k) + w_1(k)$$

Where,

k : Spatial Location (x, y) of a pixel in the image frame

$z_1(k)$: Noisy intensity of the pixel

$s\,(k)$: Noise-free intensity of the pixel

$w_1(k)$: Zero mean white Gaussian noise

- Assuming no illumination changes, no camera motion, and no changes in image acquisition parameter like camera focus, etc.

Mathematical Formulation (Contd.)

- The noise-free intensity at each pixel in the second or current frame can be modeled as a displaced value from the previous (i.e. first) frame or as an uncovered background value.

$$z_2(k) = \begin{cases} s(k - d(k)) + w_2(k), & k \notin \gamma_b \\ b(k) + w_2(k), & k \in \gamma_b \end{cases}$$

Where,

$d(k)$: non-uniform displacement vector

$b(k)$: intensity of the scene background

$w_2(k)$: zero-mean white Gaussian noise

γ_b : region of uncovered background

LRT Formulation

- Assuming that d(k) is small enough such that the first-order approximation of s(k-d(k)) is valid.

- Defining,

$$\xi(k) = z_2(k) - z_1(k)$$

and,

$$w(k) = w_2(k) - w_1(k)$$

- In this event the expression for intensity of second frame becomes,

$$z_2(k) = s(k) - g^T(k)d(k) + w_2(k)$$

Where,

$$g(k) = [g_1(k), g_2(k)]^T$$

-is the gradient vector of the intensity of the previous frame.

LRT Formulation (Contd.)

- Thus we obtain,

$$z_2(k) = \begin{cases} -g^T(k)\, d\,(k) + w(k), & k \notin \gamma_b \quad : H_1 \\ b\,(k) - s(k) + w(k), & k \in \gamma_b \quad : H_0 \end{cases}$$

- The likelihood ratio for the binary hypothesis test can be formed as:

$$\Lambda[\xi(k)] = \frac{p(\xi(k)|H_1)}{p(\xi(k)|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta = \frac{P_0}{P_1}$$

- $p(\xi(k)|H_1) = \int p(\xi(k)|H_1,d)\, p(d)\, dd$

LRT Formulation (Contd.)

- Thus the Likelihood Ratio can be formed as:

$$\Lambda[\xi(k)] = \frac{\exp\left\{\frac{1}{2}\, m^T C\, m\right\} I(\xi(k))}{2\pi |K_d|^{1/2} \int \exp\left\{\frac{-2\xi(k)q(k)+q^2(k)}{2\sigma_w^2}\right\} p(q(k))\, dq}$$

Where,

$$I(\xi(k)) = \int \exp\left\{\frac{1}{2}(d-m)^T C\, (d-m)\right\} dd$$

$m = -C^{-1}(g(k)/\sigma^2_w)\, \xi(k)$

K_d: Covariance Matrix

$C = g(k)\, g^T(k)/\, \sigma^2_w + K_d^{-1}$

$q(k) = b(k) - s(k)$

3-Ary Hypothesis Formulation

- The analysis is further extended to a 3-ary hypothesis test to separate the non-background pixels into moving and stationary pixels.

$$z_2(k) = \begin{cases} s(k-d(k)) + w_2(k), & k \in \gamma_m \\ s(k) + w_2(k), & k \in \gamma_s \\ b(k) + w_2(k), & k \in \gamma_b \end{cases}$$

γ_m: Region of moving pixels

γ_s: Region of stationary pixels

γ_b: Region of background pixels

Similarly defining ξ(k) and w(k) as in the binary case, the 3 hypothesis becomes,

$$\boxed{\xi(k) = \begin{cases} -g^T(k)d(k) + w_2(k), & k \in \gamma_m \ : H_0 \\ w(k), & k \in \gamma_s \ : H_1 \\ b(k) - s(k) + w_2(k), & k \in \gamma_b \ : H_2 \end{cases}}$$

3-Ary Hypothesis (Contd.)

- The likelihood ratios can be given as follows;

$$\Lambda_1[\xi(k)] = \frac{f\,[\xi(k)|H_1]}{f\,[\xi(k)|H_0]} \qquad \Lambda_2[\xi(k)] = \frac{f\,[\xi(k)|H_2]}{f\,[\xi(k)|H_0]}$$

$$P_1(C_{01}-C_{11})\Lambda_1[\xi(k)] \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}{\gtrless}} P_1(C_{01}-C_{11}) + P_2(C_{01}-C_{11})\Lambda_2[\xi(k)]$$

$$P_2(C_{02}-C_{22})\Lambda_2[\xi(k)] \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}{\gtrless}} P_0(C_{20}-C_{00}) + P_1(C_{21}-C_{01})\Lambda_1[\xi(k)]$$

$$P_2(C_{12}-C_{22})\Lambda_2[\xi(k)] \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}{\gtrless}} P_0(C_{20}-C_{10}) + P_1(C_{21}-C_{11})\Lambda_1[\xi(k)]$$

Performance Evaluation

- Several test image sequences were generated to evaluate the binary and 3-ary hypothesis tests.
- I have used both hypothesis tests on the images at several signal-to-noise ratios using a single measurement for classifying each pixel.
- The SNR is defined as,

$$\text{SNR} = 10\log_{10}\left[\frac{\textit{average image variance}}{\textit{noise variance}}\right] \quad d\text{B}$$

- For binary hypothesis test, ROC curves are generated at several SNRs; whereas for 3-ary hypothesis test confusion matrix is formed for the 20 dB SNR test case.

Performance Evaluation (Contd.)

- Confusion matrices are formed for several different cost matrices.
- All of the above tests require knowledge of the pdf of the difference between background and object intensity, (i.e. q (k)), in the region of the uncovered background.
- This pdf was determined by convolving the histogram of the background with the flipped histogram of the object and normalizing it.

Results & Discussion

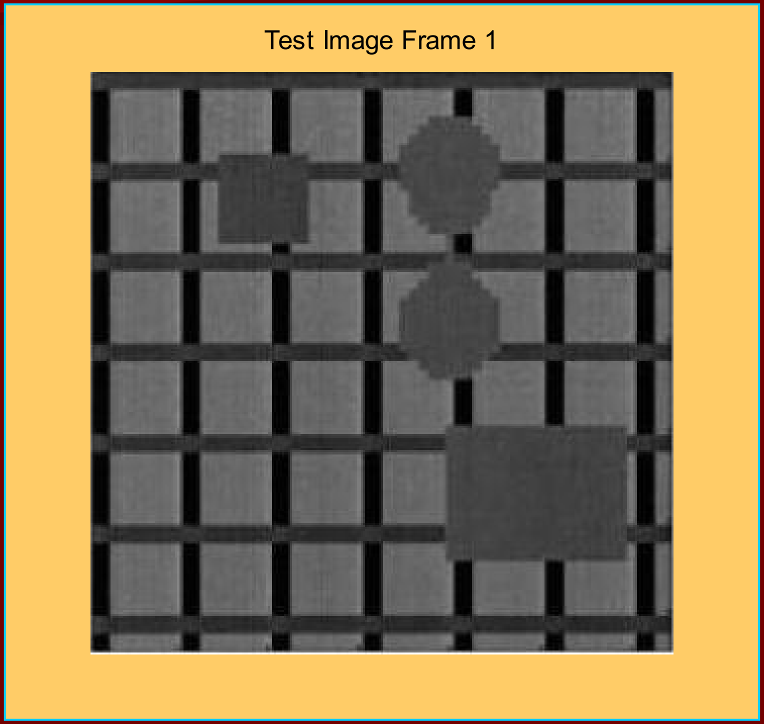
- A priori probabilities used are:

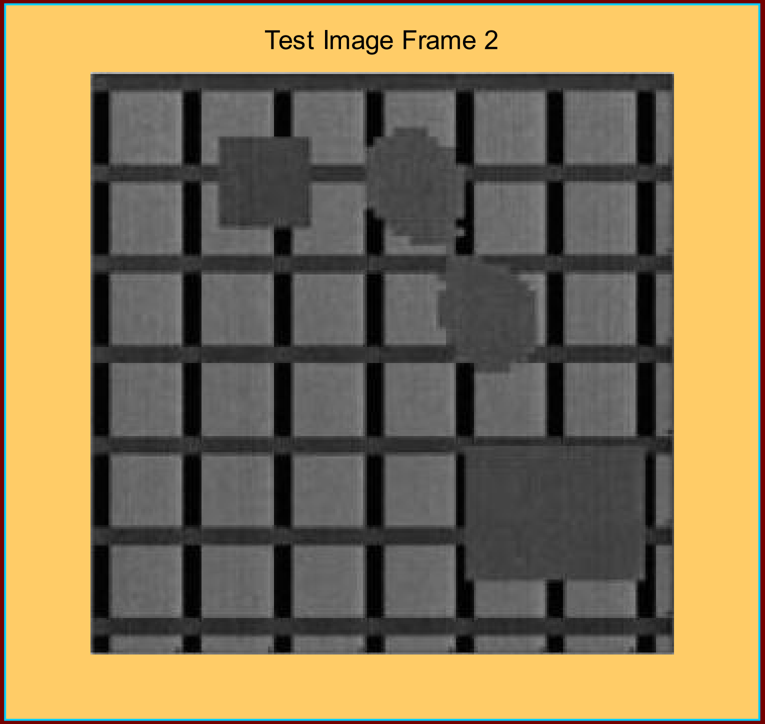
$$P = [\ P_0 \quad P_1 \quad P_2\ ]$$
$$P = [0.1 \quad 0.8 \quad 0.1]$$

- The two different cost matrices used are:

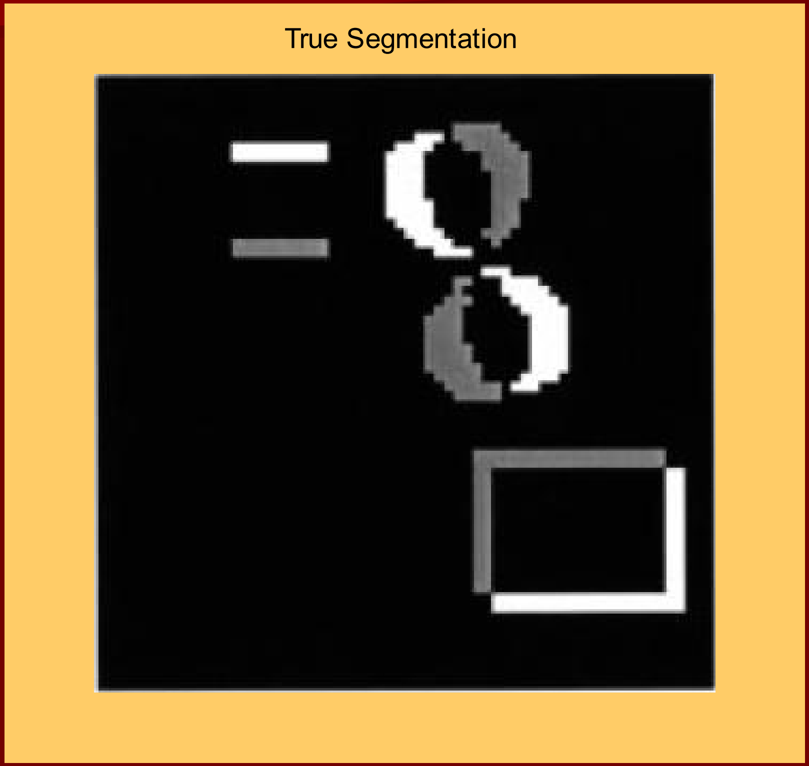
$$C_1 = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \qquad C_2 = \begin{bmatrix} 0 & 1 & 1 \\ 9 & 0 & 9 \\ 1 & 1 & 0 \end{bmatrix}$$

Results & Discussion (Contd.)

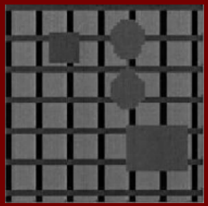


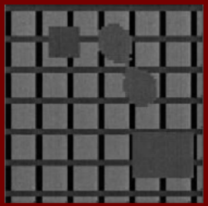


Results & Discussion (Contd.)



White: Moving Pixels
Black: Stationary Pixels
Gray: Uncovered Background Pixels

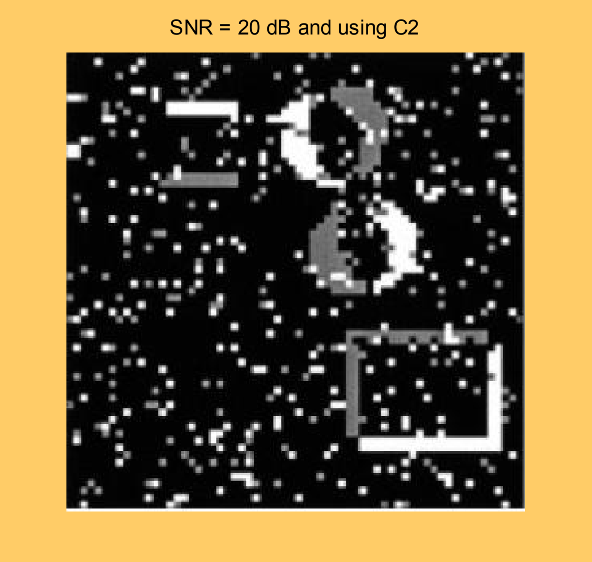




Results & Discussion (Contd.)

True / Detected	Moving	Stationary	Uncovered Background
Moving	84	1	6
Stationary	8	98	13
Uncovered Background	8	1	81

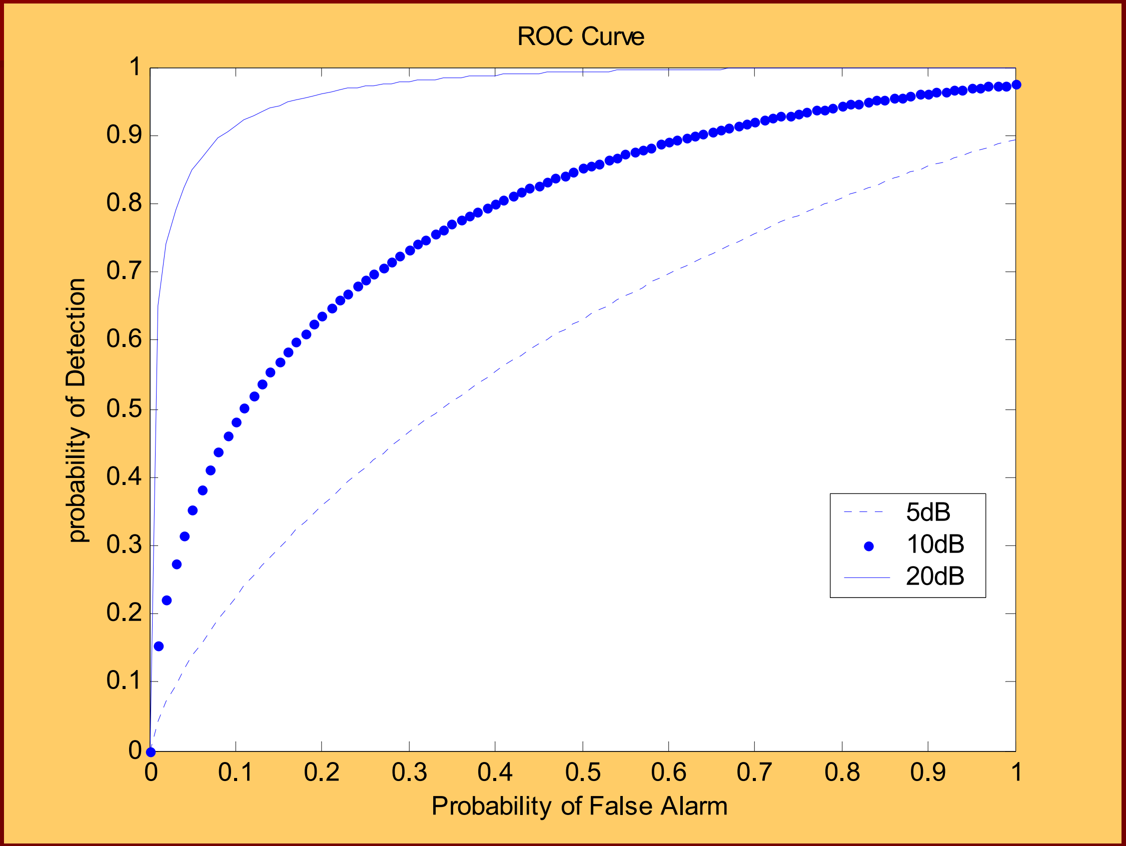
In percentage at SNR 20 dB using C1



True / Detected	Moving	Stationary	Uncovered Background
Moving	89	6	7
Stationary	3	89	4
Uncovered Background	8	5	89

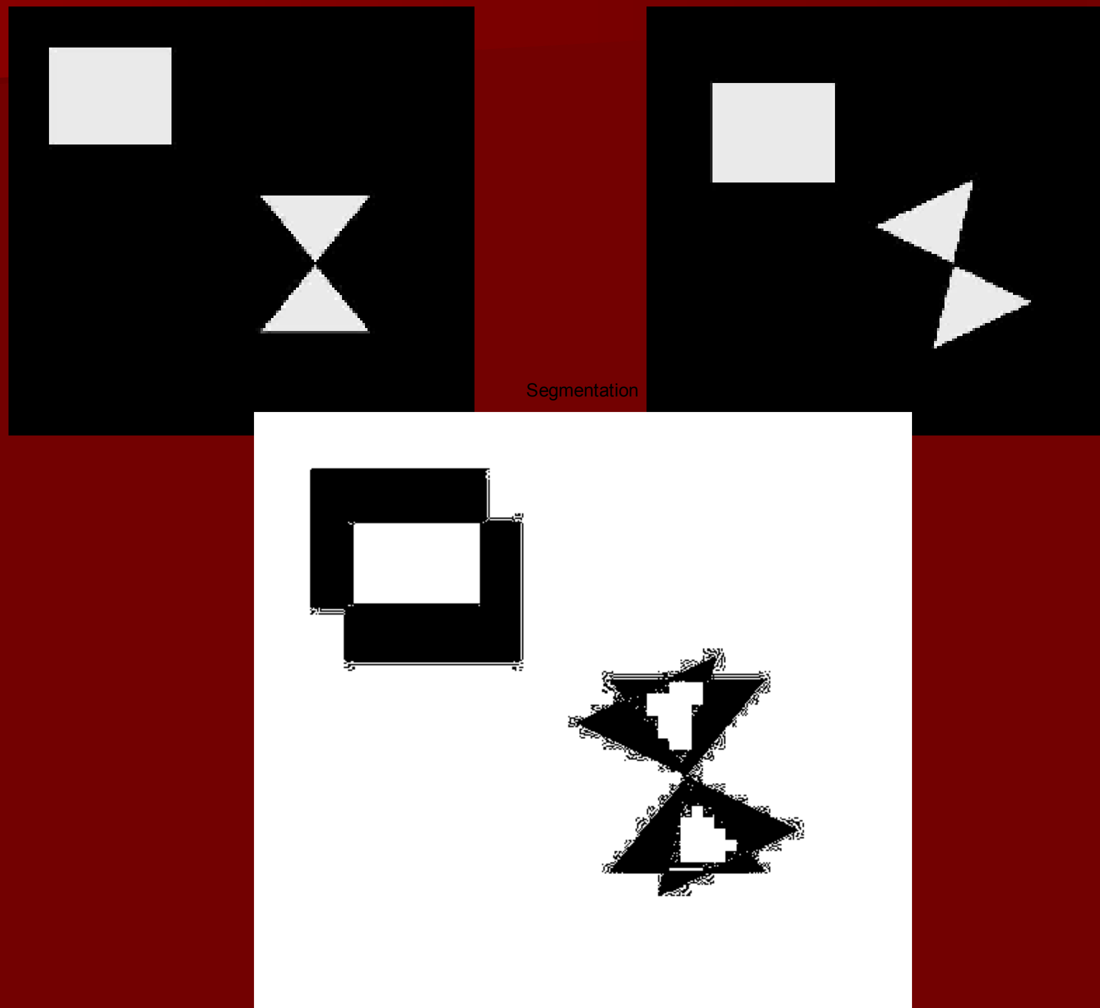
In percentage at SNR 20 dB using C2

ROC Curve



ROC Curve
probability of Detection
Probability of False Alarm
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
5dB
10dB
20dB

Another Example



Conclusions

- In this project, I have presented a binary and ternary hypothesis test, based on Bayes decision criterion.
- The goal of the project is the detection of moving, stationary, and uncovered-background pixels in image sequences.
- The basic application of this method is in the video-teleconferencing and videophone.

Future Work

- Testing of this method, on real time teleconferencing image sequences.
- Active contour algorithm (snake algorithm) can be used to segment the person contour in an image frame.
- Detection of the signal in presence of various types of noises, such as additive white Gaussian noise (AWGN), color noise, etc.

References

- "Non-uniform image motion estimation using Kalman filtering", N. M. Namazi, P. Penafiel, and C. M. Fan, IEEE Trans. Image Processing, Vol. 3, pp 191-212, 1989.
- "On regularization, formulation and initialization of the active contour models (snakes)", K. F. Lai and R. T. Chin, in Asian conf. Computer vision, Osaka, Japan, Nov. 1993, pp 542-545.
- "Detection Theory – Application and Digital Signal Processing", R. Hippenstiel, CRC Press, 2002
- Zivkovic, Z.; Petkovic, M.; van Mierlo, R.; van Keulen, M.; van der Heijden, F.; Junker, W.; Rijnierse, E.; "Two video analysis applications using foreground/background segmentation"; Visual Information Engineering, 2003. VIE 2003. International Conference on , 2003 Pages:310 – 313
- ECE 8433 – Class Notes.

Question & Answers