ROBUST DETECTION, CLASSIFICATION AND CLUSTERING

Progress over period 11/95 - 11/01

Alfred Hero
Dept. of EECS
University of Michigan

Principal Objective: To develop weak-target detection/classification/clustering algorithms which are robust to target and clutter variability yet maintain highest possible discrimination capability.

Methods: CFAR target detection, iterative estimation, graph theoretic clustering algorithms, optimal compression for detection tasks.

0.1 RESEARCH ACCOMPLISHMENTS

- **Detection algorithms for inhomogeneous clutter**: Max invariant and GLR tests (Hero&Kim, IEEE Trans Image Proc. (2001) [**?**]).

- **Accelerated EM and SAGE ML/PML algorithms**: proximal-point with Kullback penalty (Chretien&Hero, IEEE Trans. Inform. Theory (2000) [**?**]).

- **Theory and application of *k*-shortest graphs**: entropy estimation, robust clustering, image registration, (Hero&Michel, IEEE Trans. Inform. Theory (1999) [**?**], Hero&etal IEEE Sig. Proc. Magazine (2002) [**?**])

- **Compression for detection tasks**: high rate distortion theory Gupta&Hero (2001) IEEE Trans. Inform. Theory (2002) [**?**])

0.2 Adaptive Detection of Deep Hide Targets

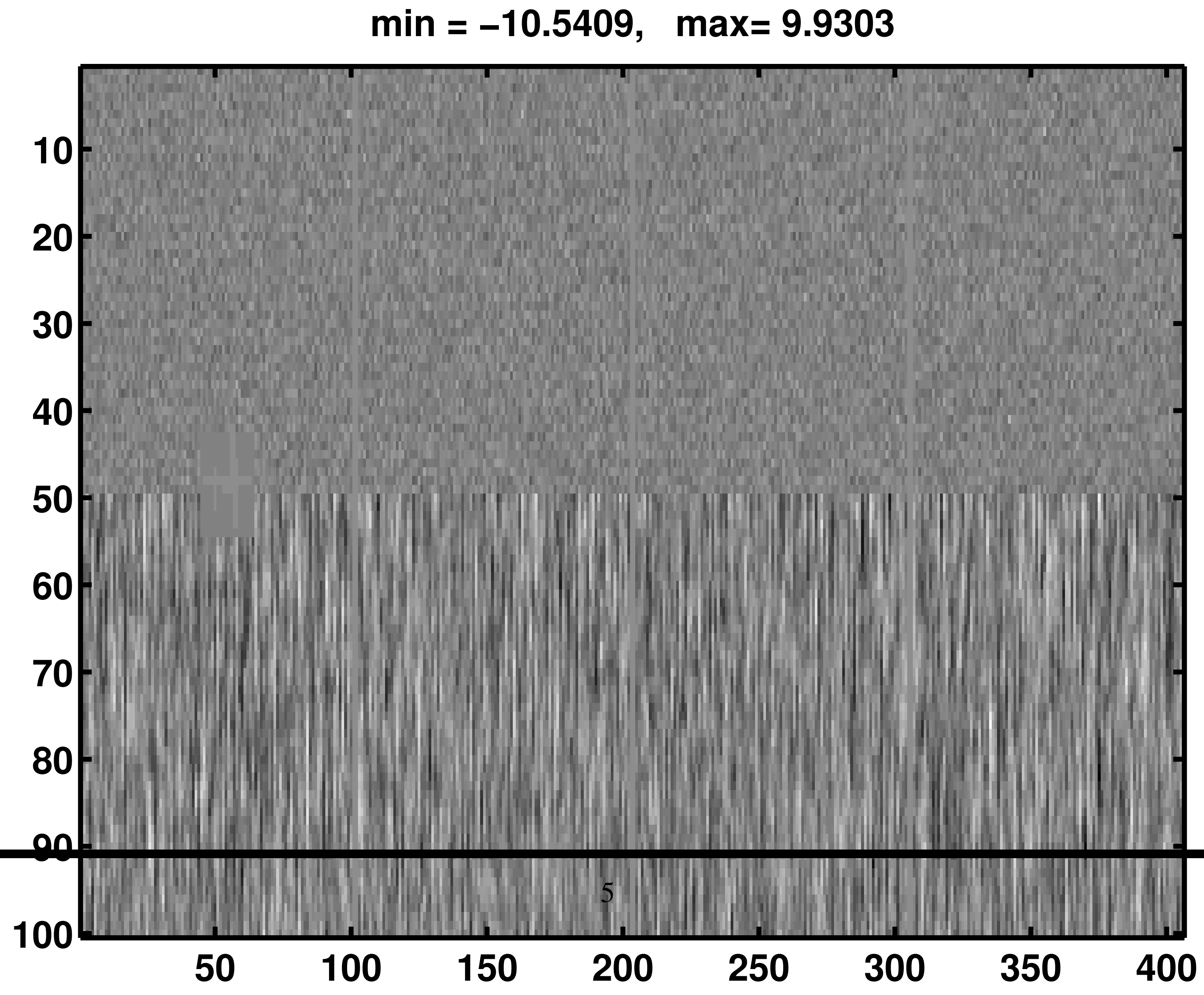
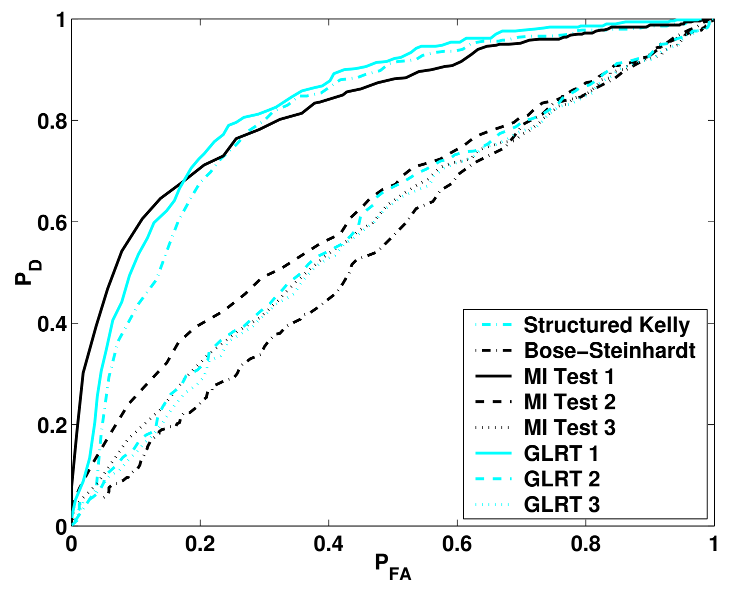


Figure 1: Known deep hide target on clutter boundary

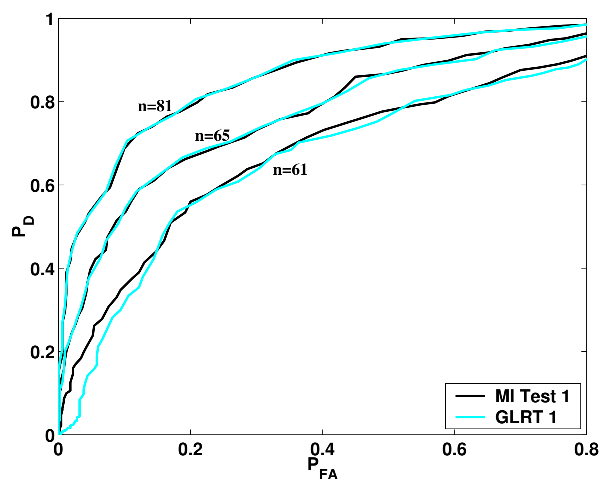
Objective: Adaptive target detection in structured unknown clutter.

Methods: GLR and maximal invariant tests for structured MANOVA

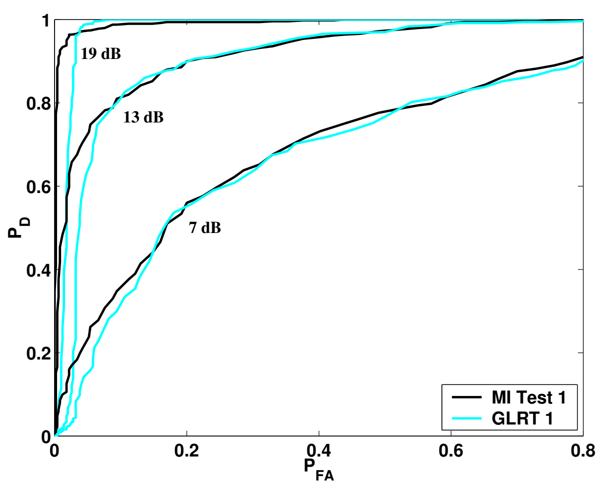


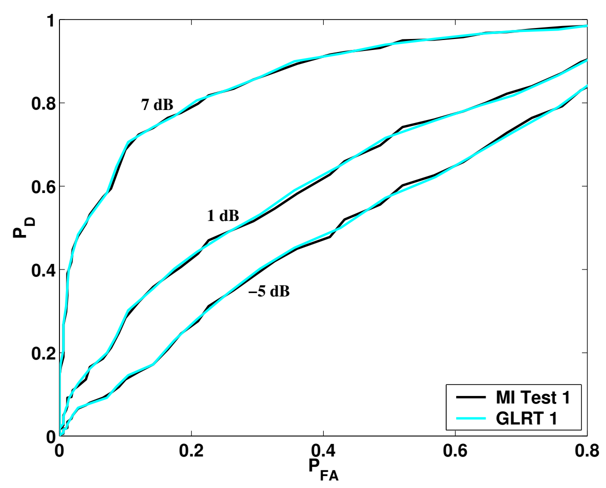
Scenario

$$SNR = 22dB\ (SNR_A = 11dB\ /\ SNR_B = 22dB)$$
$$m_A = 50\ /\ m_B = 50\ ,\ n = 51$$



$(SNR = 7dB)$





$(n = 61)$

$(n = 81)$

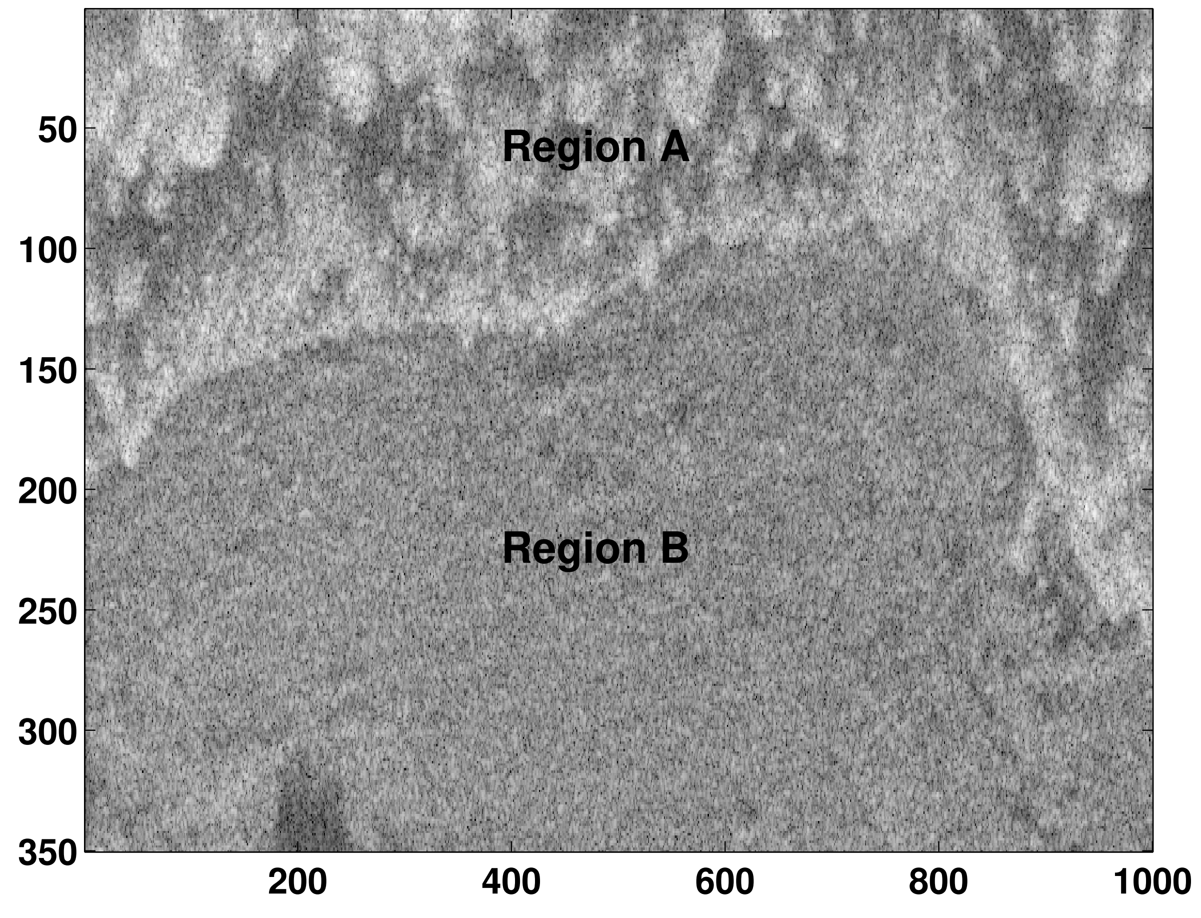


Figure 2: SAR clutter image with a single target (e) straddling the boundary at column 305.

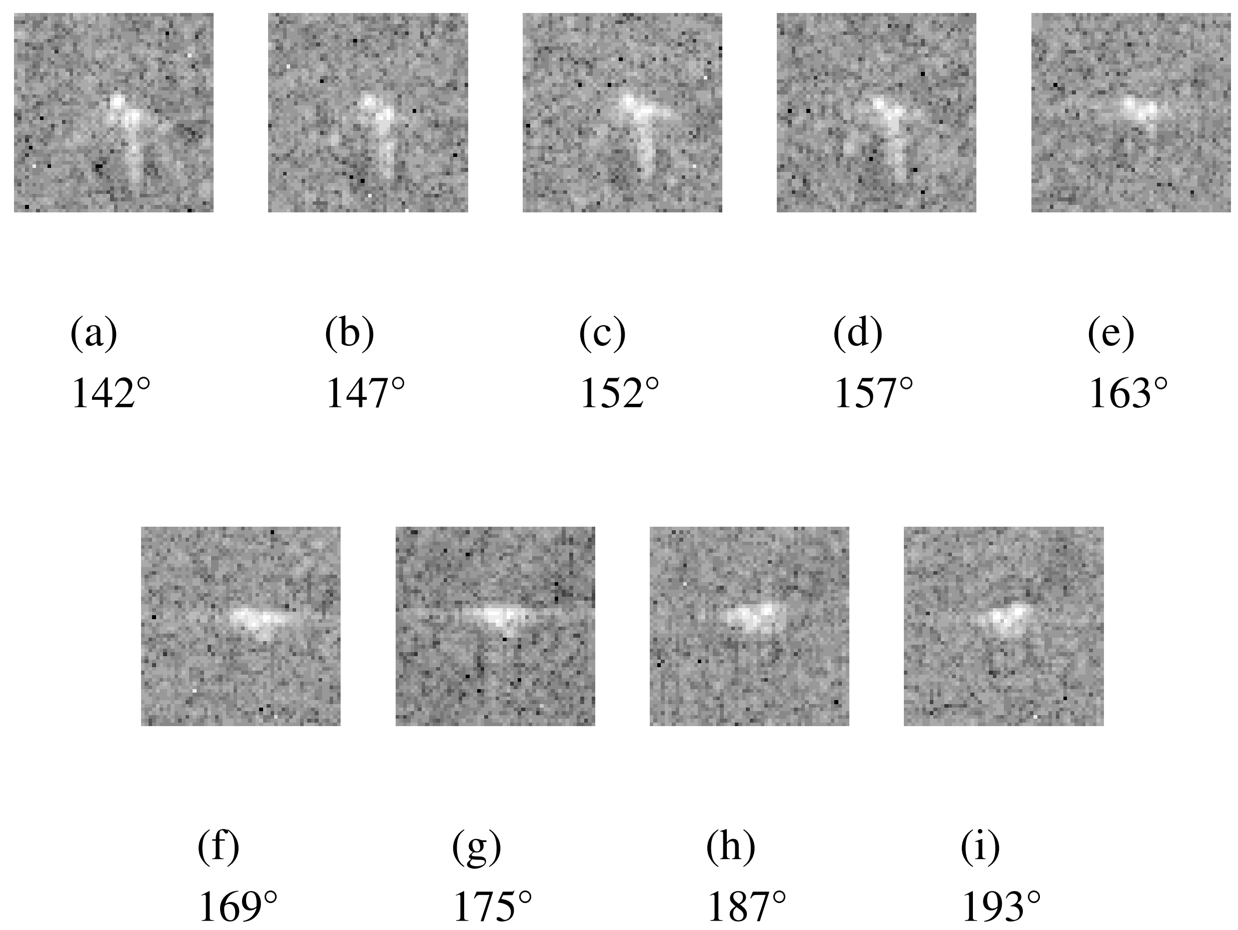


Figure 3: SLICY canonical target images (54×54) at elevation 39° and different azimuth angles. Image in (e) is inserted in Figure 2.

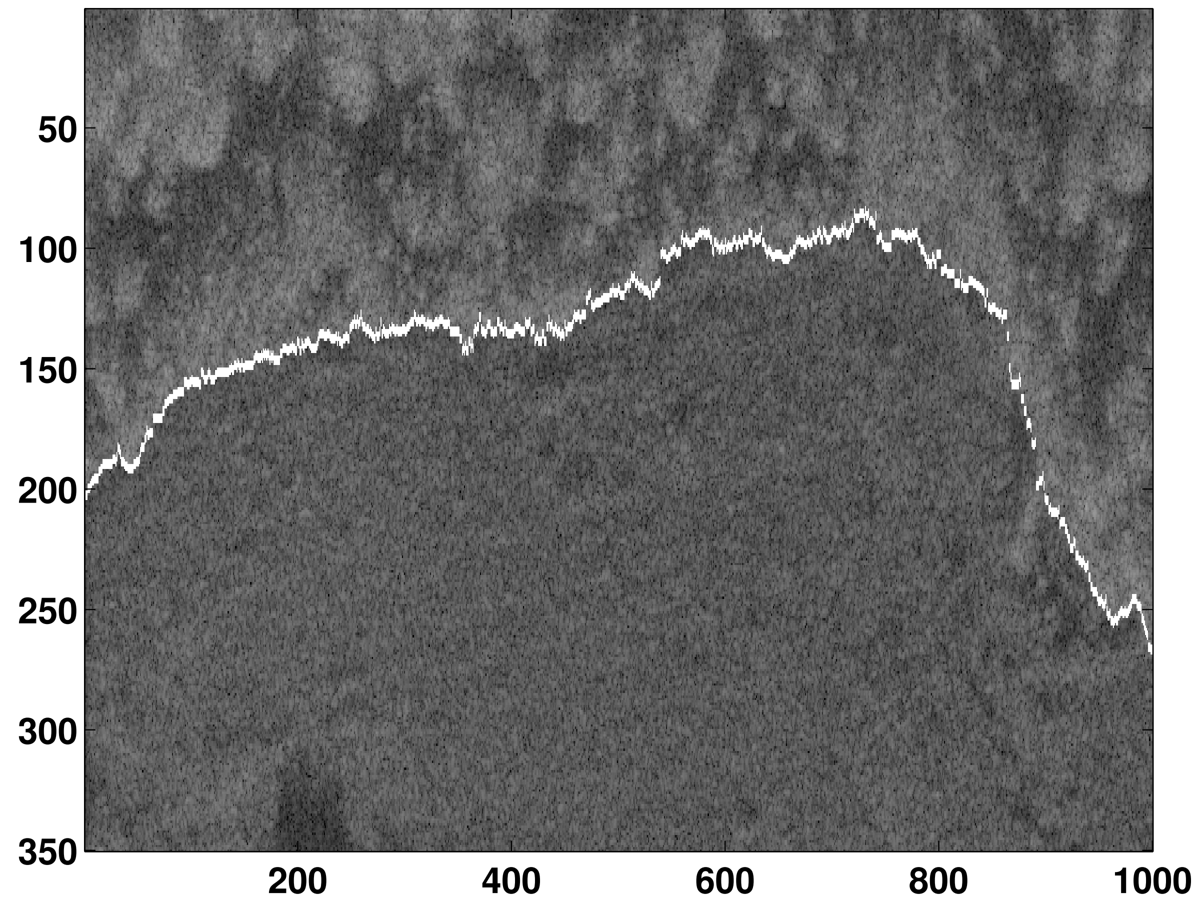


Figure 4: Hand-extracted boundary superimposed on the initial image in Figure 2.

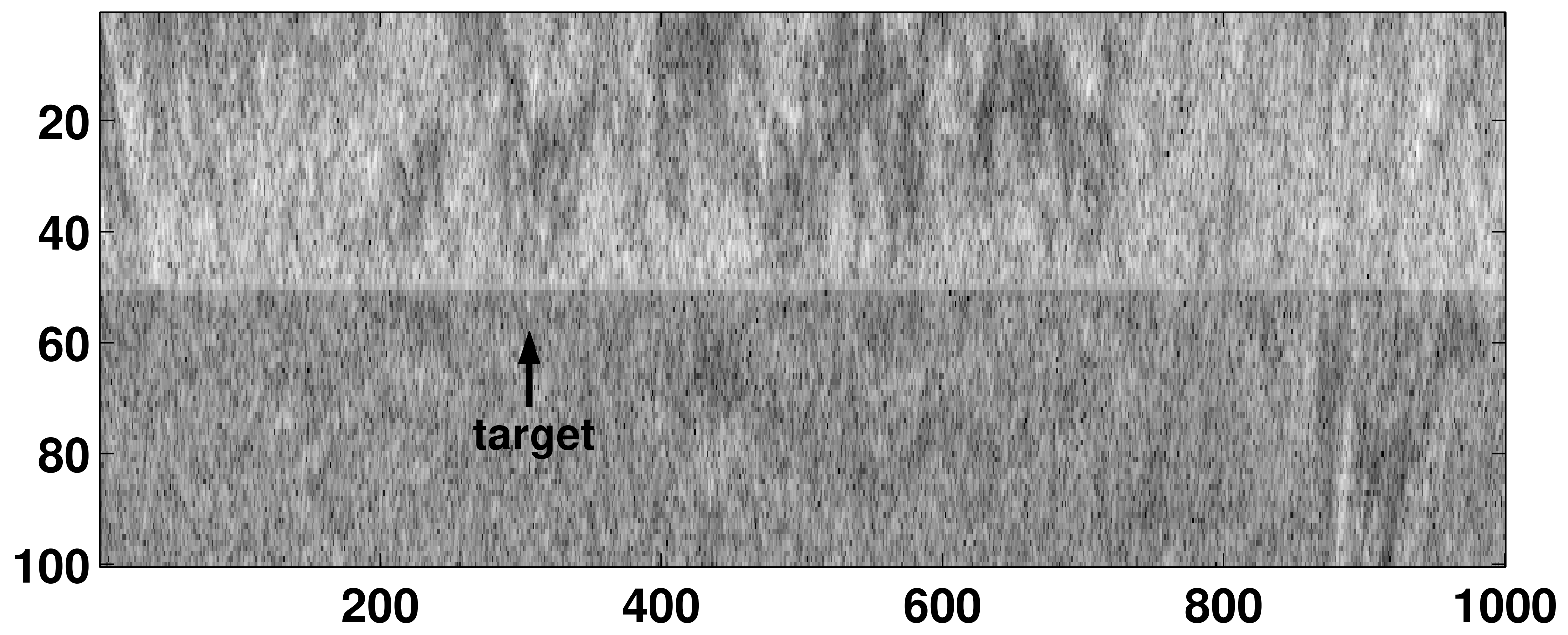


Figure 5: Image realigned along the extracted boundary. SLICY target is located at column 305 with $|a| = 0.015$. This target is just above the minimal detectable threshold for the three tests investigated in Figure **??**.

Hypothesis testing problem:

$$H_0 \quad : \quad \mathbf{Y} = \mathbf{N}$$

$$H_1 \quad : \quad \mathbf{Y} = \mathbf{S}\,\mathbf{a}\,\mathbf{B} + \mathbf{N}$$

- $\mathbf{S} = [\underline{s}_1, \ldots, \underline{s}_p]$ = known $m \times p$ matrix of spatial target signatures
- $\mathbf{a}$ = unknown $p \times p$ matrix
- $\mathbf{B}$ known $p \times n$ indicator matrix of target-containing chips
- $\mathrm{vec}\{\mathbf{N}\} \sim \mathcal{N}_{mn}(\underline{0}, \mathbf{R} \otimes \mathbf{I}_n)$
- $\mathbf{R}$ unknown **block diagonal** clutter covariance

GLR Test:

$$\Lambda(\mathbf{Y}) = \frac{\max_{\mathbf{a} \neq 0, \mathbf{R} > 0} f(\mathbf{Y}; \mathbf{a}, \mathbf{R})}{\max_{\mathbf{a} = 0, \mathbf{R} > 0} f(\mathbf{Y}; \mathbf{a}, \mathbf{R})} \underset{H_0}{\overset{H_1}{\gtrless}} \eta$$

0.3 Proximal-Point/EM Algorithms

Objective: maximize the convex (penalized) log likelihood

$$\ln f(Y;\, \underline{\theta}) - \beta P(\underline{\theta})$$

Challenges: ensuring fast convergence rate, low computation per iteration, stability, monotonicity.

<u>Our Solution</u>: (Chretien&Hero:IT01)

Develop new class of stable, monotonic and rapidly convergent hybrid EM algorithms: Kullback-proximal-point (KPP) methods.

Computational form of Kullback-PPA:

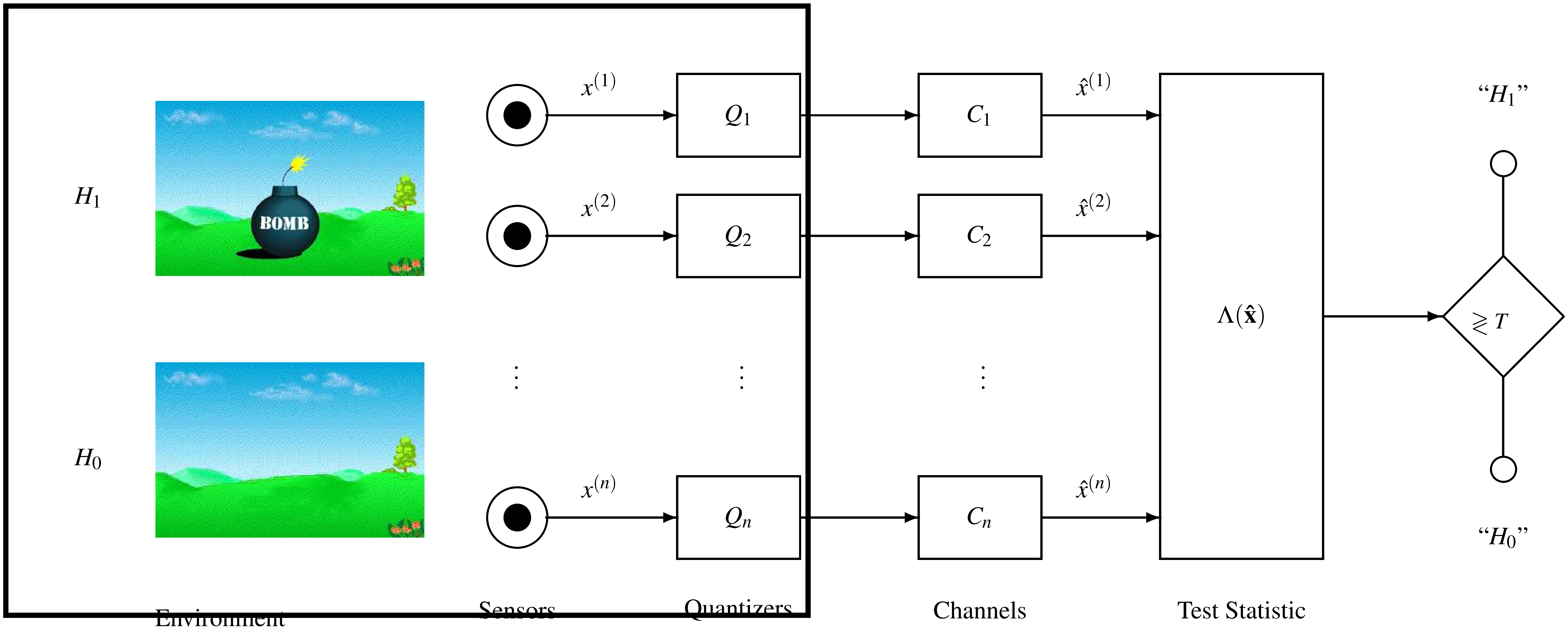
$$\underline{\theta}^{k+1} = \text{argmax}_{\underline{\theta}} \left\{ (1-\lambda_k) \ln f(Y;\underline{\theta}) + \lambda_k Q(\underline{\theta} \mid \underline{\theta}^k) \right\}, \qquad k = 1,2,\ldots$$

Properties: (Chretien&Hero:SIAM98)

- Kullback-PPA has monotone likelihood property for any $\lambda_k > 0$
- Bundle mechanism (conjugate subgradient) (LeMarechal:75) can be applied for non-differentiable $f(Y;\underline{\theta})$, $Q(\underline{\theta};\underline{\theta}^k)$
- Obtain superlinear convergence rate for differentiable case
- Under local quadratic approximation to $\ln f(Y;\underline{\theta})$ Kullback-PPA becomes hybrid EM/Newton algorithm
- Kullback-PPA generalizes to coordinatewise optimization: hybrid SAGE/Newton

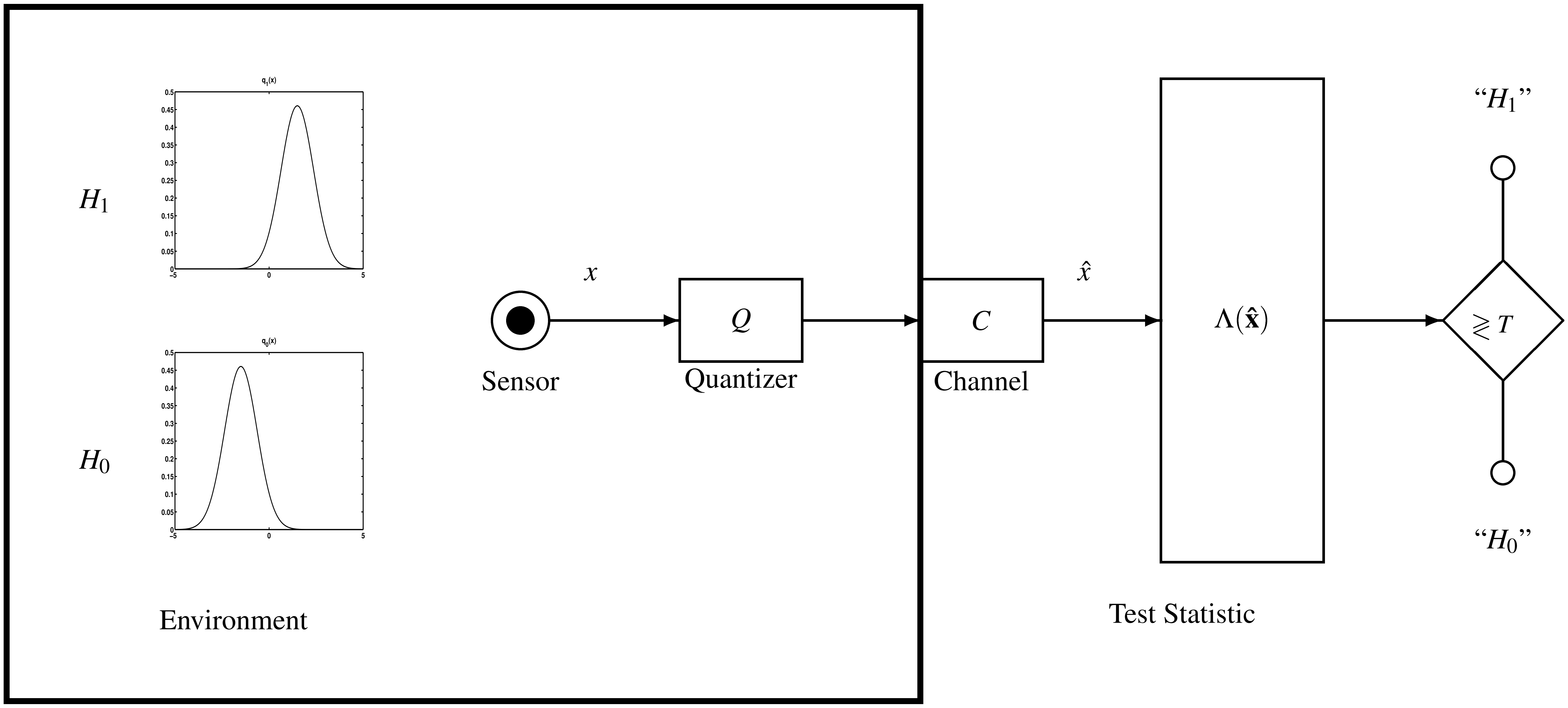
0.4 Distributed quantization in a sensor net

Objective: Observe $[\hat{x^{(1)}}, \ldots, \hat{x^{(n)}}] = Q(\mathbf{x})$ and decide between H_0 and H_1

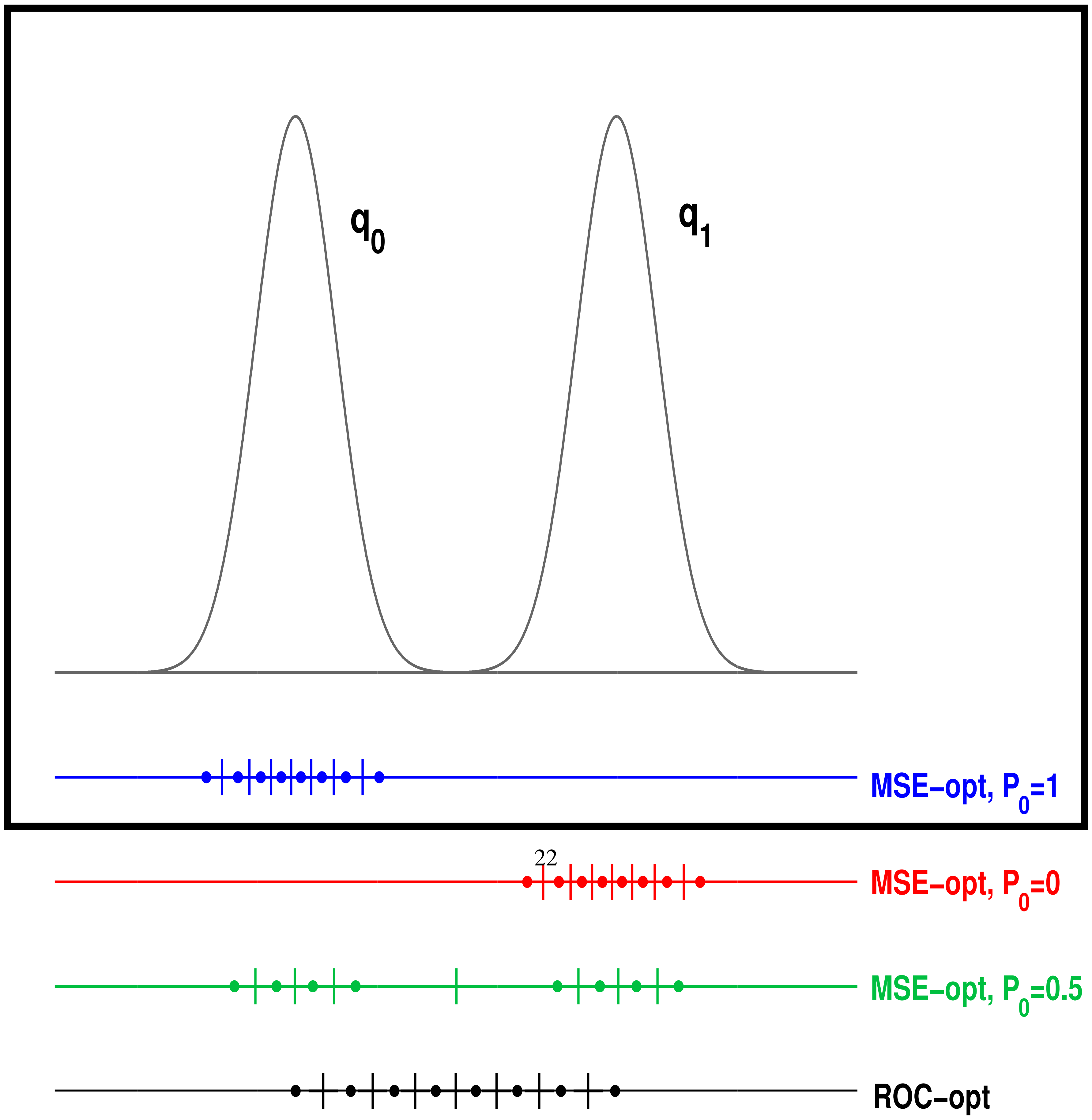

H_1
H_0
BOMB
$x^{(1)}$
$x^{(2)}$
$x^{(n)}$
Q_1
Q_2
Q_n
C_1
C_2
C_n
$\hat{x}^{(1)}$
$\hat{x}^{(2)}$
$\hat{x}^{(n)}$
$\Lambda(\hat{\mathbf{x}})$
$\gtrless T$
"H_1"
"H_0"
Environment
Sensors
Quantizers
Channels
Test Statistic

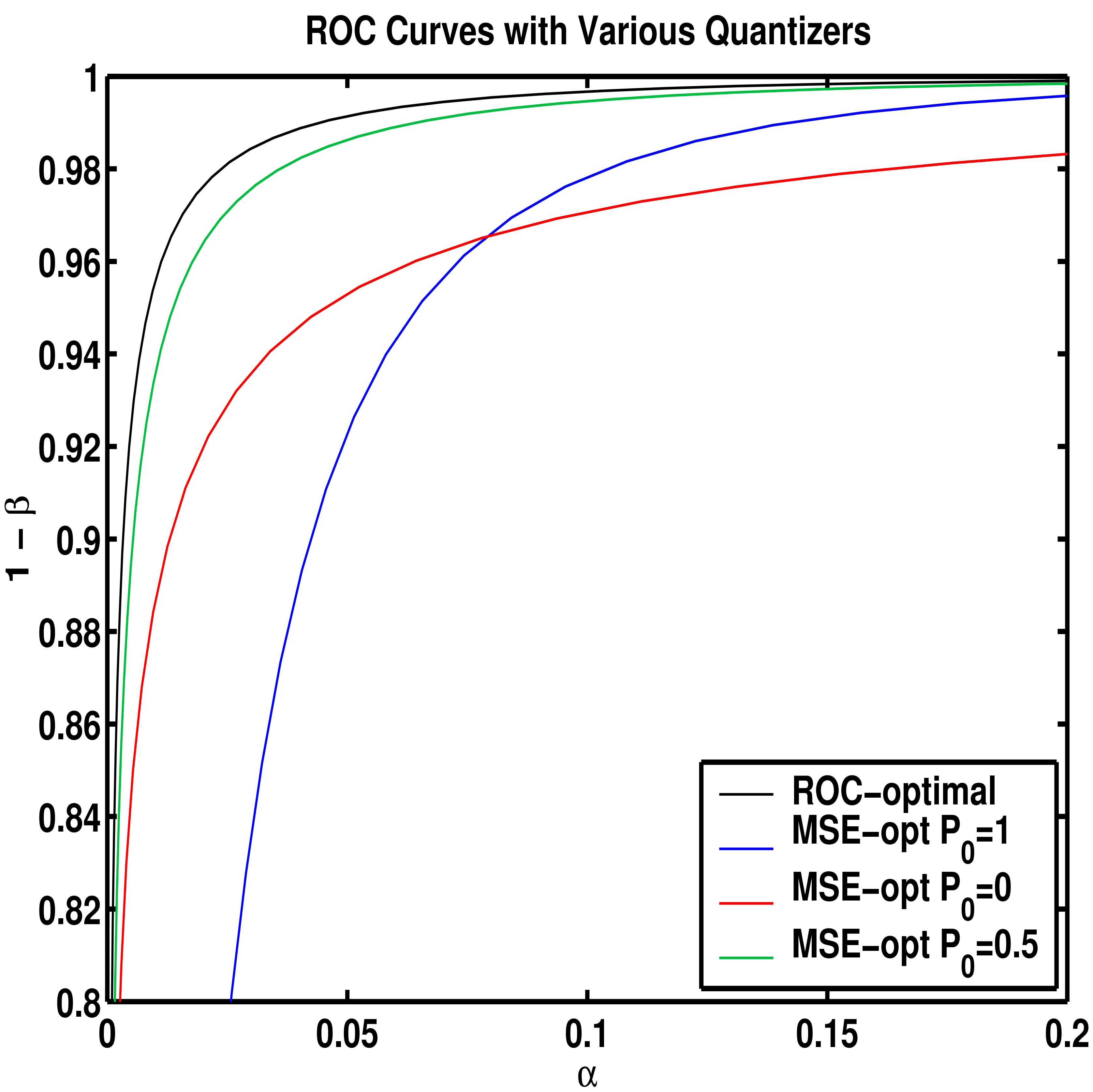
Hypothesis testing from Q/VQ data

Objective: Observe $\hat{x} = Q(x)$ and decide between H_0 and H_1


H_1
H_0
Environment
x
Sensor
Q
Quantizer
C
Channel
$\hat{x}$
$\Lambda(\hat{\mathbf{x}})$
Test Statistic
$\gtrless T$
“H_1”
“H_0”

ROC Performance of Various Quantizers


q0
q1
MSE−opt, P0=1
MSE−opt, P0=0
MSE−opt, P0=0.5
ROC−opt


ROC Curves with Various Quantizers
1 − β
α
0
0.05
0.1
0.15
0.2
0.8
0.82
0.84
0.86
0.88
0.9
0.92
0.94
0.96
0.98
1
ROC−optimal
MSE−opt P0=1
MSE−opt P0=0
MSE−opt P0=0.5