ROBUST DETECTION, CLASSIFICATION AND CLUSTERING

Progress over period 11/95 - 11/01

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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

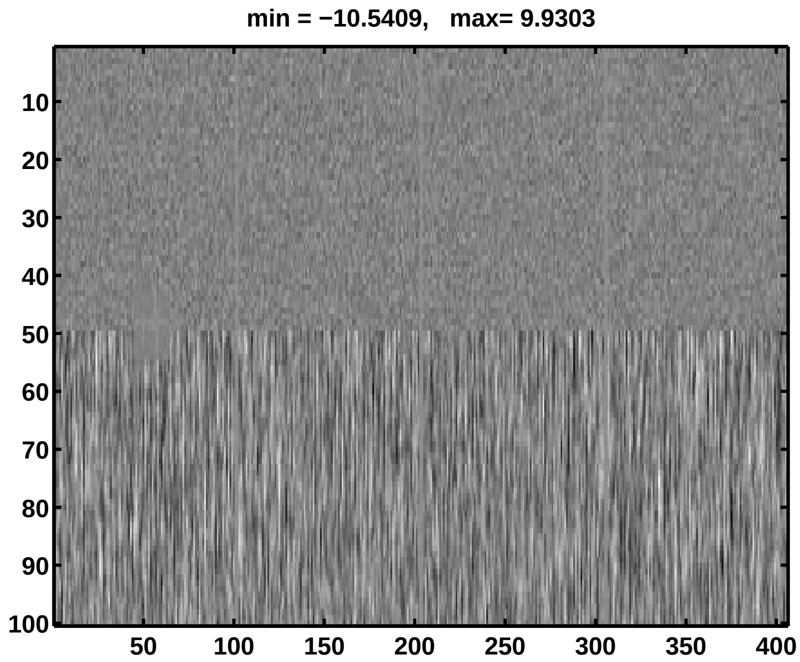

Figure 1: Known deep hide target on clutter boundary

Objective: Adaptive target detection in structured unknown clutter.

Methods: GLR and maximal invariant tests for structured MANOVA

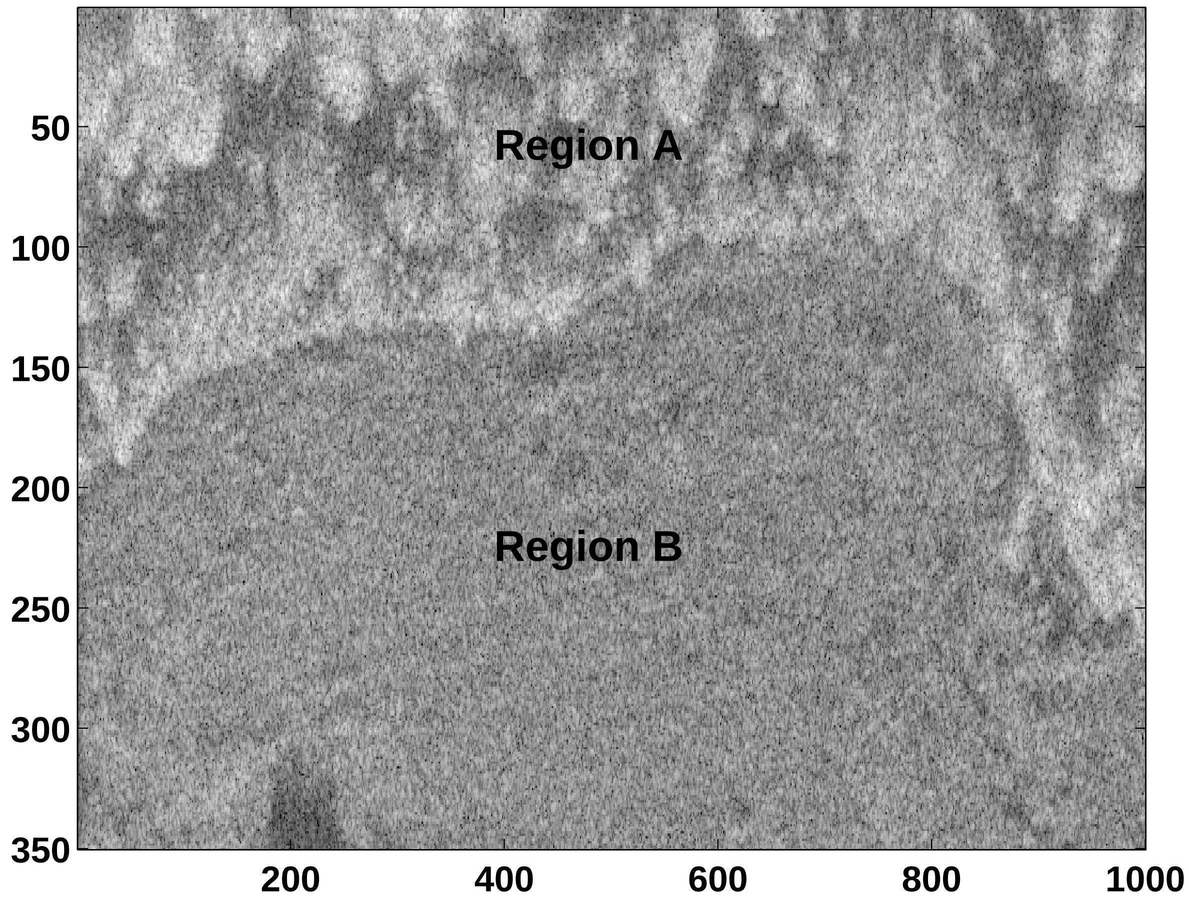

Figure 2: SAR clutter image with a single target (e) straddling the boundary at column 305.

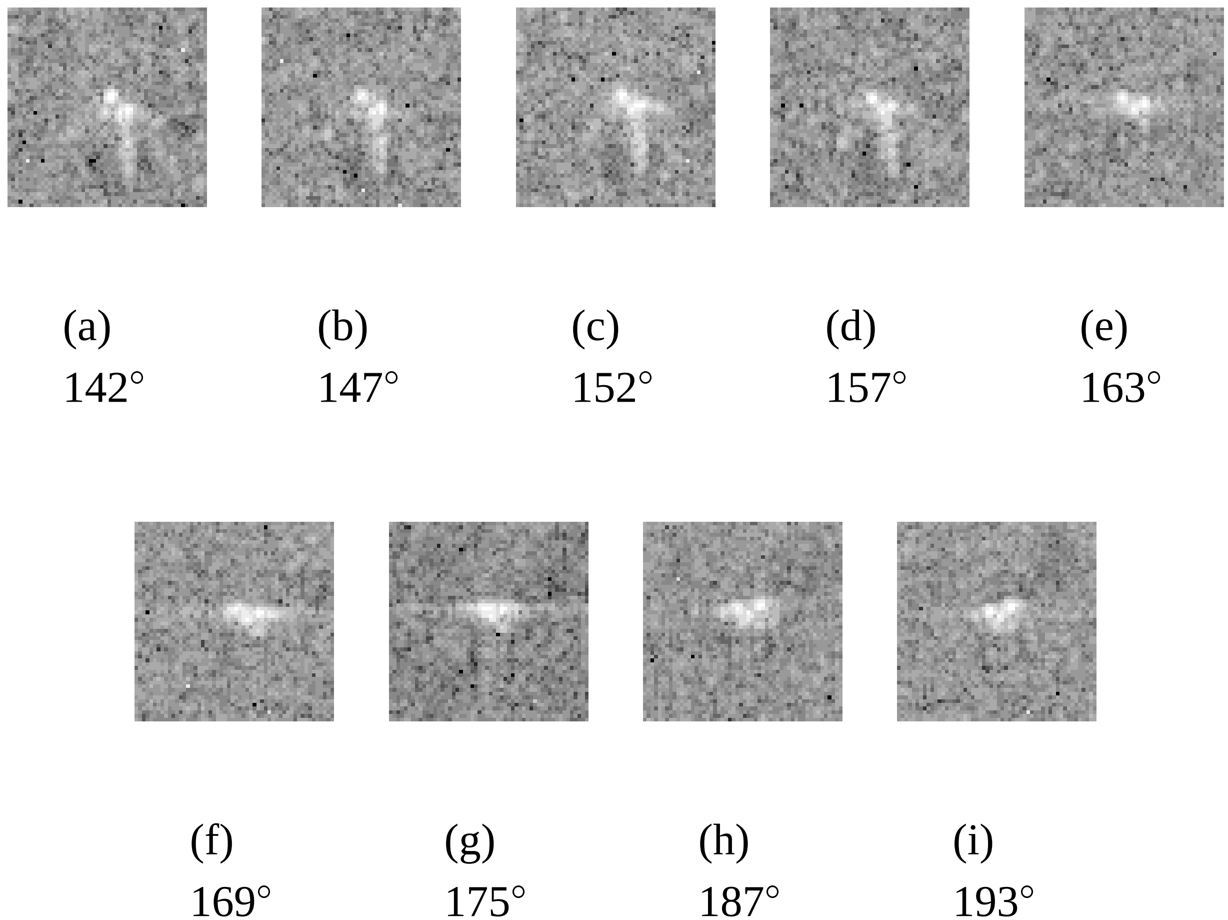

Figure 3: SLICY canonical target images (54×54) at elevation 39° and different azimuth angles. Image in (e) is inserted in Figure 2.

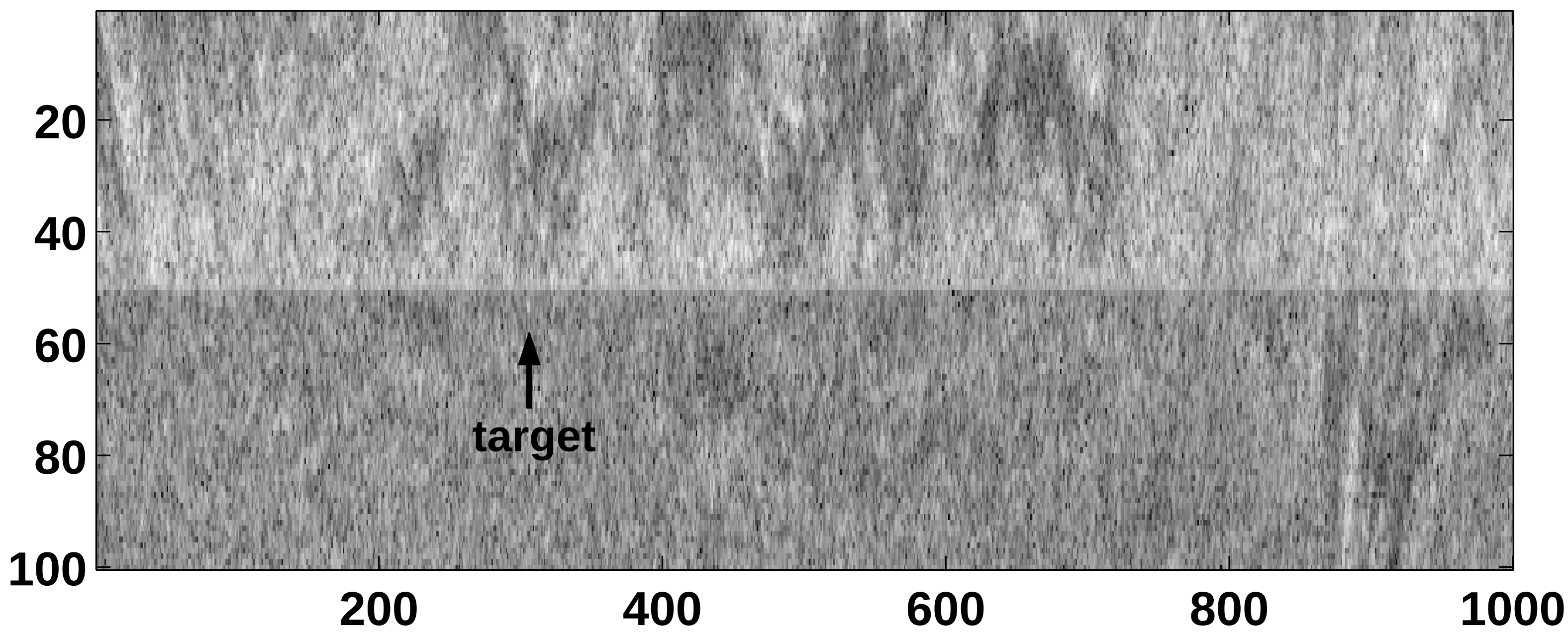

Figure 4: Image realigned along the extracted boundary. SLICY target is located at column 305 with $|a| = 0.015$. This target is just above the minimal detectable threshold for the three tests investigated in Figure **??**.

Minimum detectable thresholds

Test	$\lvert a \rvert$	
	$(n-1=250)$	$(n-1=200)$
MI test 1	1.454×10^{-2}	0.609×10^{-1}
GLR 1	1.462×10^{-2}	1.042×10^{-1}
Structured Kelly	1.407×10^{-2}	1.049×10^{-1}

Table 1: Minimum detectable amplitudes for detection of the target at the correct location.

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.

Our Solution: (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:

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

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