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Bayesian Compressive Sensing in Radar Systems

CS in Radar Processing

Bayesian Approach: closed form, Monte-Carlo Methods, ...

Conclusions and Future Work

Radmila Pribić
Sensors, Advanced Developments Delft

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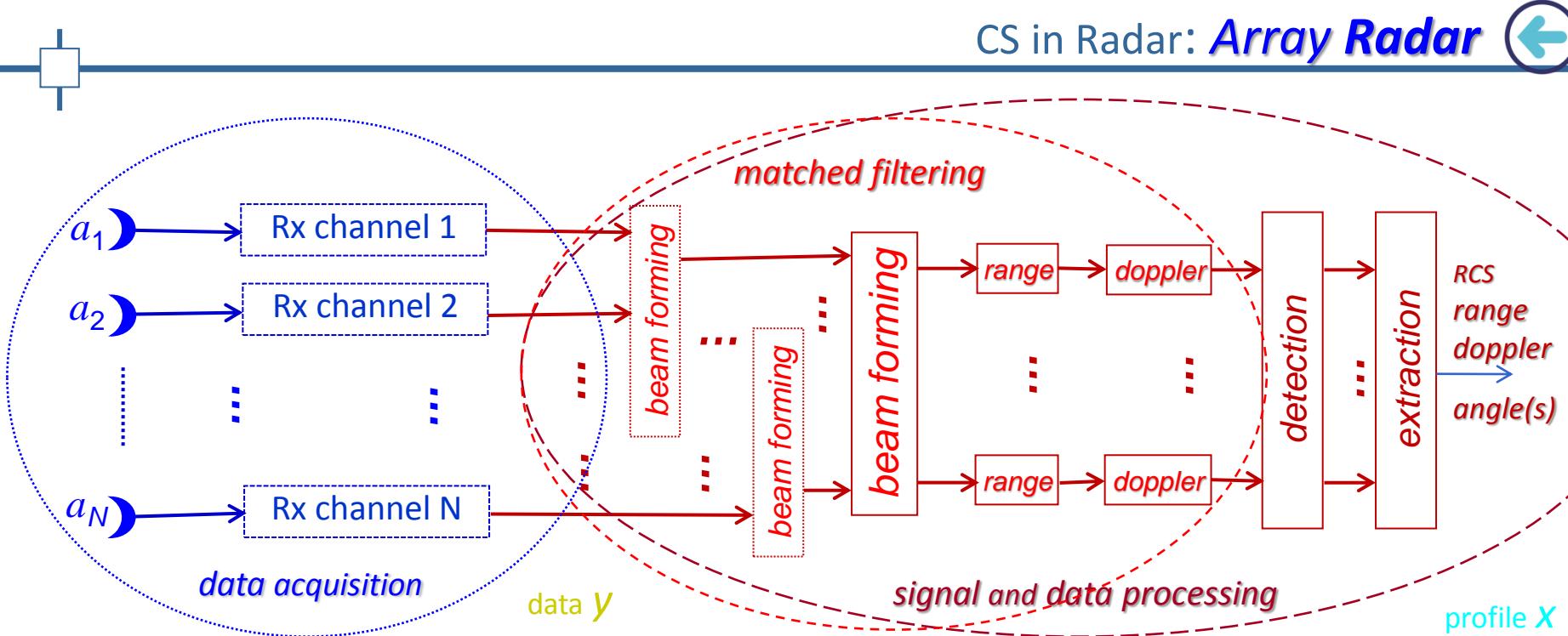
THALES NEDERLAND B.V. Sensors, Advanced Developments Delft
CoSeRa 17-19 September, 2013: Bayesian CS in Radar Systems

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΛΕΥΚΩΣΙΑΣ

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Data sizes **growing** fast with:

- **higher resolution** in:
 - **range**: wider signal bandwidth (denser sampling, faster ADC, higher data rates)
 - **doppler**: longer observation time (more samples)
 - **angle(s)**: more antenna elements (more samples)
- **more**: sensors (sensor/antenna array, MIMO, ...), modalities (RF, acoustic, visual), ...

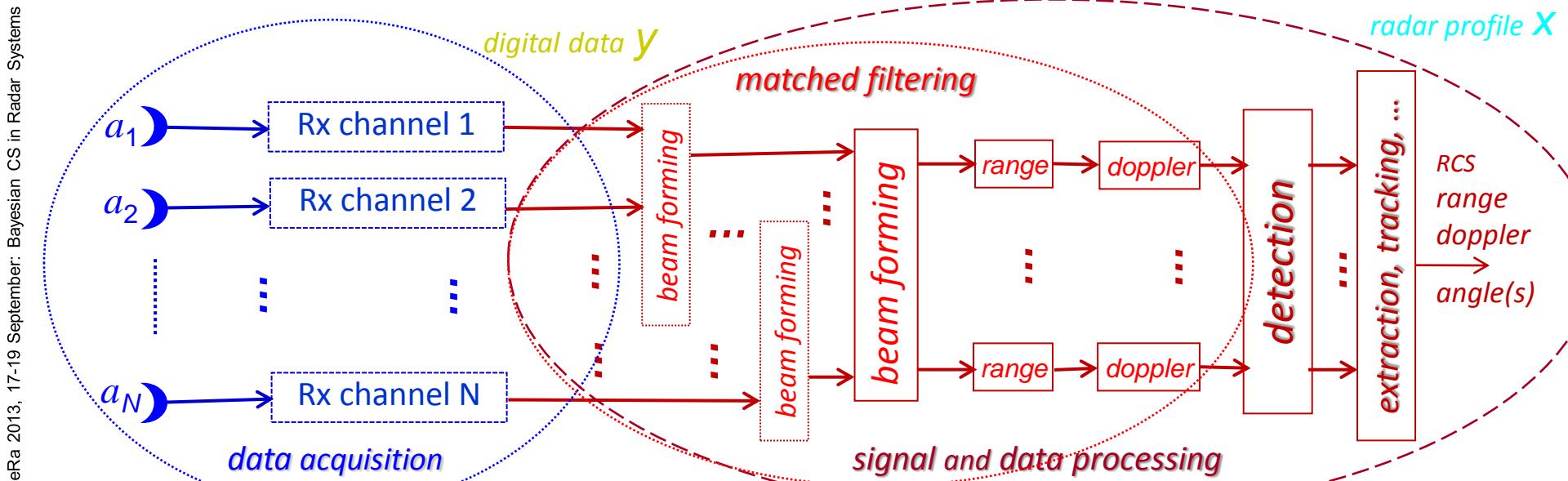
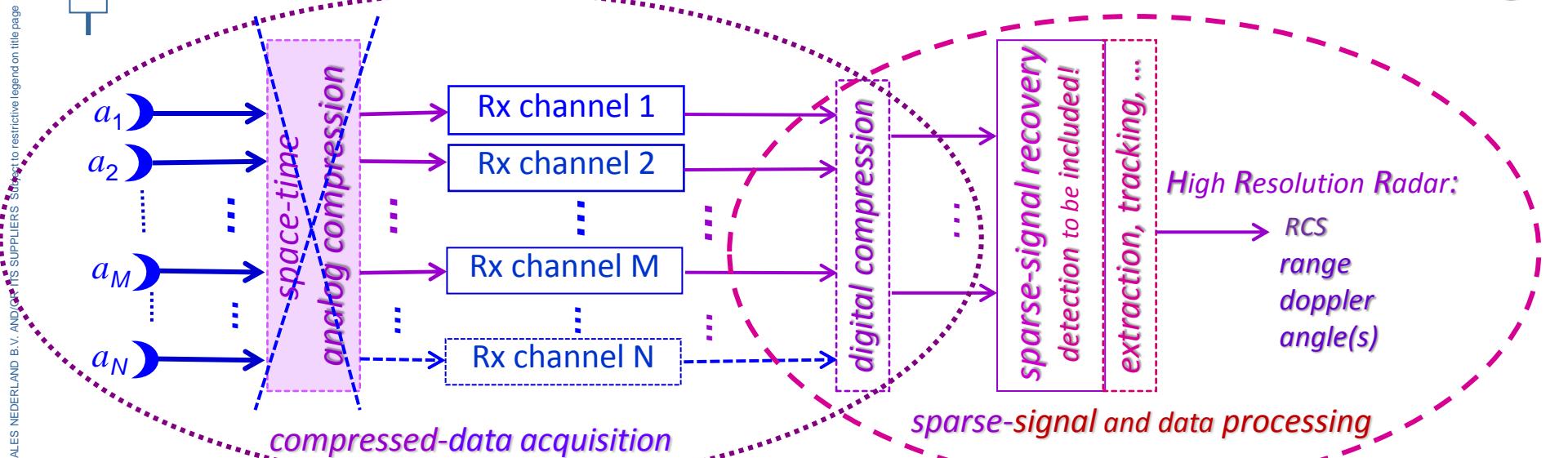
large data size & low information density!



CS in radar!

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CS in Radar: *Array Radar with(out) CS*





measurements \mathbf{y} = echo-model \mathbf{A} profile \mathbf{X}

- ✓ CS foundations!
- sparse \mathbf{X}
- incoherent compression \mathbf{B}

$$\mathbf{By} = \mathbf{BAx} \quad \mathbf{y} = \mathbf{Ax} \quad \Rightarrow \quad \text{sparse-}\mathbf{x} \text{ recovery: } \min_{\mathbf{x}} (\|\mathbf{x}\|_1) \text{ s.t. } \mathbf{y} = \mathbf{Ax}$$

✓ Noise \mathbf{z} : $\mathbf{By} = \mathbf{BAx} + \mathbf{Bz}$ $\Rightarrow \min_{\mathbf{x}} (\|\mathbf{y} - \mathbf{Ax}\|_2^2 + \alpha_p \|\mathbf{x}\|_1)$

$$\mathbf{z} \longleftrightarrow \mathcal{CN}(0, \sigma^2 I)$$

Clutter \mathbf{e} : $\mathbf{By} = \mathbf{BAx} + \mathbf{Bz} + \mathbf{BAe}$ $\Rightarrow \min_{\mathbf{x}} (\|\mathbf{y} - \mathbf{Ax}\|_2^2 + \alpha_p \|\mathbf{x}\|_1 + ?)$

$$\mathbf{e} \longleftrightarrow \mathcal{CN}(0, C) \text{ or non-}\mathcal{CN}: SIRV (\mathcal{CN} + \text{Weibull}, \dots)$$

Extended targets \mathbf{x} : \mathbf{x} is a patch, i.e. occupies more than a single resolution cell!

$$\min_{\mathbf{x}} (\|\mathbf{y} - \mathbf{Ax}\|_2^2 + \alpha_p \|\mathbf{x}\|_1 + \alpha_g \|\mathbf{Gx}\|_1 + ?)$$

...

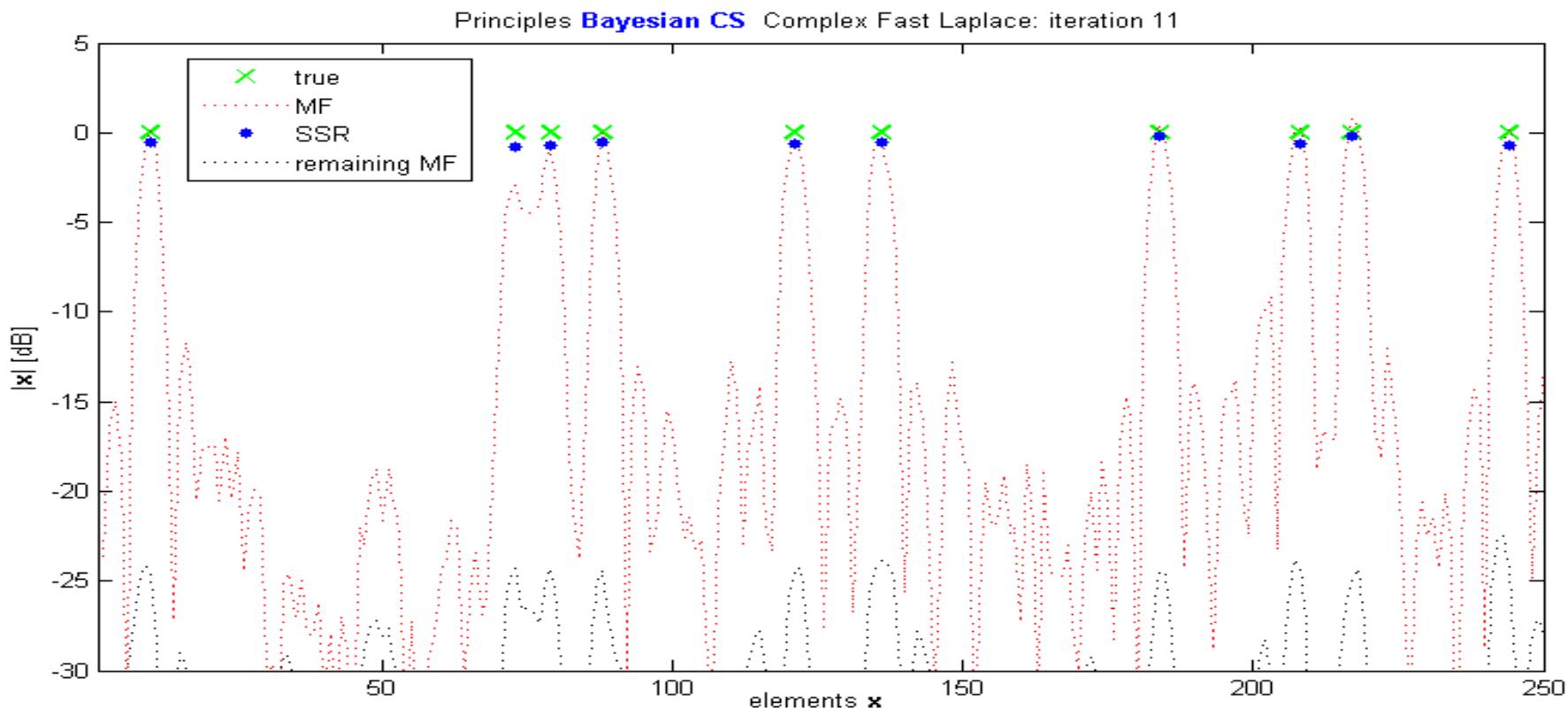


Bayesian Sparse-Signal Recovery

Woodward, P. M. (1953)

Probability and information theory, with applications to radar, Pergamon.

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{z} \quad \xleftarrow{\text{---}} \quad \mathbf{x} \leftrightarrow \text{sparse}() \quad \mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{z} \quad \mathbf{z} \leftrightarrow \mathcal{CN}(\mathbf{0}, \sigma^2 \mathbf{I})$$



Babacan et al. (2010) *Bayesian CS using Laplace Priors*.
IEEE Trans. Image Processing, Vol 19/no.1, pp.53-63

Hubert J. Flisijn (2011) *Implementation of CS in Radar Systems*.
MSc thesis, University of Twente.

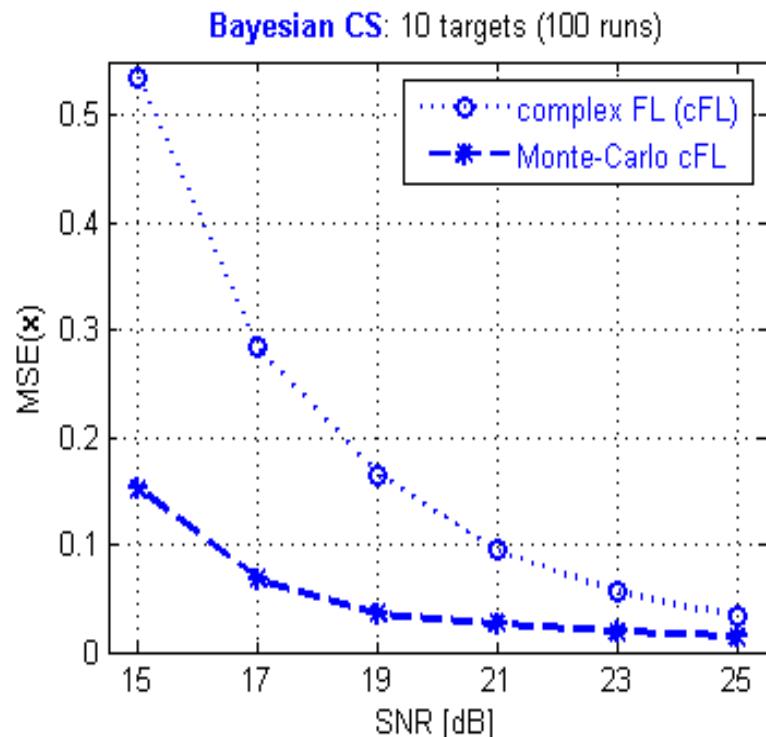


Realistic Bayesian CS in Radar: no restrictions to Gaussian likelihood, prior or compression!

Practical Bayesian CS using MC methods:

- directly estimating significant elements in \mathbf{x}
- a single combination of best elements in \mathbf{x}
- only elements with strong detection probability
- model-based and detection-driven SSR

- I. Initialize residuals $\mathbf{y}_{\text{res},1} = \mathbf{y}$ and profile remains $\mathbf{x}_{\text{res},1} = \mathbf{x}_{\text{MF}}$
- II. For each iteration k till stopping (or up to K_{\max})
 - i. Perform an MC realization l (up to L)
 - Draw an element $n_{k,l}$ from its *importance density*
 - Estimate its weight $w_{k,l}$, and bias $b_{k,l}$
 - ii. Select $n(k)$ from all $\{n_{k,l}\}$ with best weight from $\{w_{k,l}\}$
 - iii. Estimate amplitude $x_{n(k)}$ and *posterior* of best $n(k)$
 - iv. Update model-based residuals $\mathbf{y}_{\text{res},k+1} = \mathbf{y}_{\text{res},k} - X_{n(k)} \mathbf{a}_{n(k)}$
 - v. Update model-based remains $\mathbf{x}_{\text{res},k+1} = \mathbf{x}_{\text{res},k} - X_{n(k)} \mathbf{A}^H \mathbf{a}_{n(k)}$

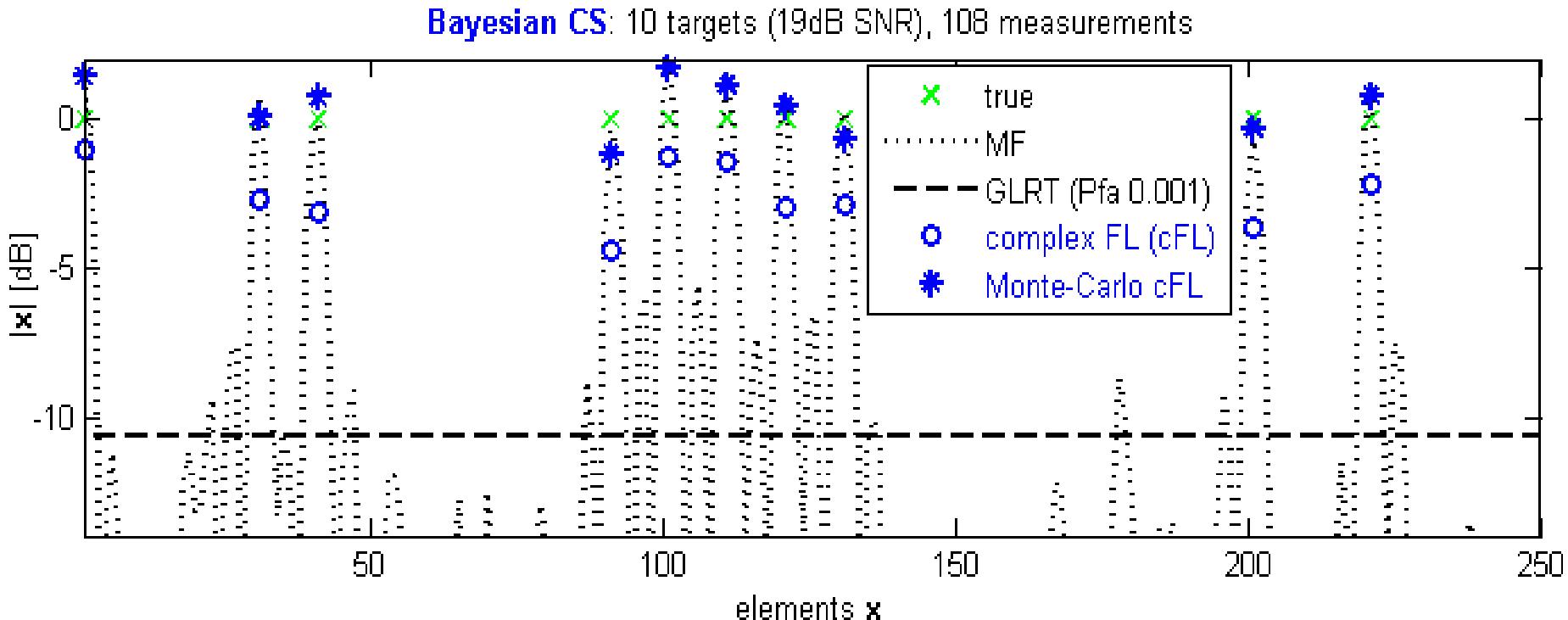


Initial Bayesian CS using MC methods:

- combinatorial reconstruction of the whole signal

Kyriakides I. and Pribić R. Bayesian CS Using Monte Carlo Methods, EUSIPCO 2013.

Kyriakides I., Pribić R., Sar H. and At N. Grid Matching in MC-BCS, FUSION 2013.

Sparse Signal Recovery in Radar: *model-based and detection-driven!*

Future work on SSR using Monte-Carlo methods:

- refining stopping criteria w.r.t. sparsity, noise, fixed false alarms, available time, ...
- optimizing performance and computations (sparsity/detection strategy, grid, bias, ...)
- evaluating other priors, likelihoods: on simulated and real data



Bayesian CS

- most convenient for radar stochastic signal processing
- elegant and practical refinement of familiar MF: model based and detection driven
- promising implementation in real time on GPU (straight echo models)!
- to be flexible to realistic/any likelihood or priors : Monte-Carlo (MC) methods!
- MC-BCS: direct estimation of a single combination of significant elements!
 - model based: greedy use of radar point-spread functions
 - detection driven: promoting sparsity via optimal detection strategy
 - MSE performance comparable if not better!

Future work

- Optimization of performance and computations of the MC-BCS algorithm
- Stochastic behavior before/after SSR (MF + Detection), Estimation, Tracking (PF), ...
- Grid-Based Choices (Estimation): Free, Prior, Irregular, Matched, ...
- non Gaussian: clutter, other priors on radar signals or their data acquisition, ...
- Real measurements: micro Doppler, small/slow targets in sea clutter, ...

Thanks!

Questions?