

# DoA estimation via MT-BCS exploiting multiple-snapshots

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## Abstract

In this report, an innovative strategy for the estimation of the directions of arrival of signals impinging on linear arrays of electromagnetic sensors has been assessed. Starting from a sparse representation of the problem solution, the DoA estimation problem has been addressed by means of a methodology based on the BCS paradigm. A customized implementation exploiting the measurements collected at multiple time instants (multiple-snapshots) providing robust and very accurate estimates when correlating the information from multiple snapshots has been validated.

## MT-BCS DoA estimation

**GOAL:** The goal of this section is the analysis of the performances of the MT-BCS method for the DoA estimation with  $W > 1$  snapshots. The performances of the method are compared with the standard single-task BCS (ST-BCS) and with the ROOT-MUSIC and ESPRIT algorithms.

$$\hat{\underline{x}}_h^{(ave)} = \frac{1}{W} \sum_{w=1}^W |\hat{\underline{x}}_h(t_w)| \quad (1)$$

being  $W$  the number of snapshots and  $h \in \{ST - BCS, MT - BCS\}$ . The main difference between the *ST* and *MT BCS* formulations is that in the second case the non-zero elements of the estimated vectors  $\hat{\underline{x}}_h(t_w)$  are forced to be in the same locations.

### Analysis vs number of snapshots $W$

#### Simulation Parameters

- Scenario
  - BPSK signals ( $E_l^{inc} \in \{-1, 1\}$ )
  - Number of incident signals:  $L = 2$
  - Signal directions:  $\underline{\theta} = \{0, 7\}$  [deg]
  - Signal to noise ratio:  $SNR = 7$  dB (equivalent to a  $SNR = 4$  dB if the literature's definition is taken into account)
- Array parameters
  - Elements spacing:  $d = 0.5\lambda$
  - Number of elements:  $M = 10$
- MT-BCS parameters
  - Number of angular locations:  $K = 181$
  - $a = 3.162$
  - $b = 3.981 \times 10^1$
- BCS parameters
  - Number of angular locations:  $K = 181$
  - $\sigma_0^2 = 4.642 \times 10^{-1}$
  - **Number of snapshots:**  $W \in [1, 25]$

- Simulation

- Number of independent realizations  $Q = 150$  (the noise and the signal amplitudes are random, while the DoAs are fixed)

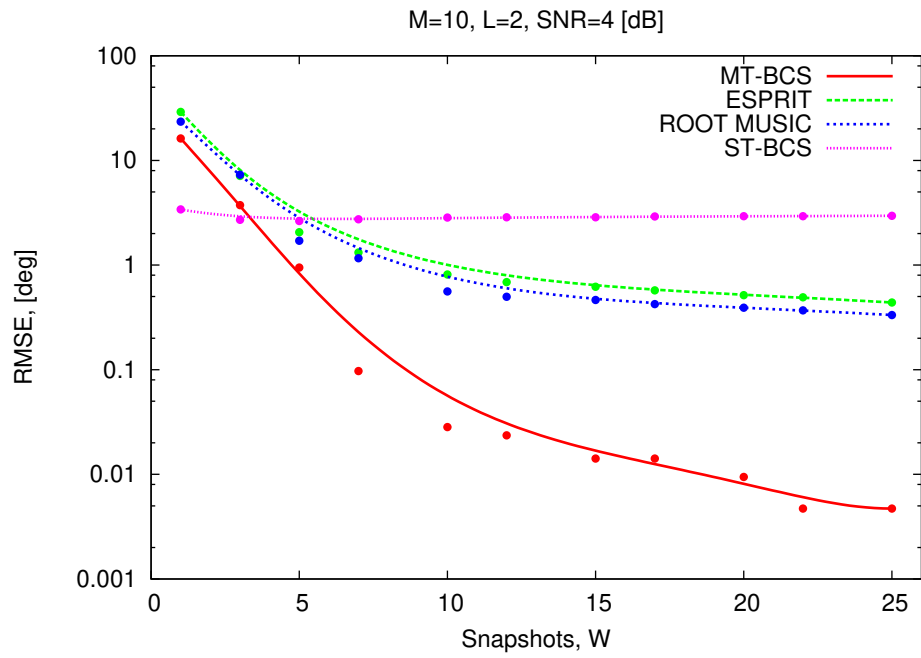


Figure 1:  $RMSE$  vs the number of snapshots  $W$ .

## Analysis vs SNR

### Simulation Parameters

- Scenario
  - BPSK signals ( $E_l^{inc} \in \{-1, 1\}$ )
  - Number of incident signals:  $L = 2$
  - Signal directions:  $\underline{\theta} = \{0, 7\}$  [deg]
  - **Signal to noise ratio:**  $SNR \in [-5, 20]$  dB ( $SNR \in [-8, 17]$  dB if the literature's definition is taken into account)
- Array parameters
  - Elements spacing:  $d = 0.5\lambda$
  - Number of elements:  $M = 10$
- MT-BCS parameters
  - Number of angular locations:  $K = 181$
  - $a = 3.162$
  - $b = 3.981 \times 10^1$
- BCS parameters
  - Number of angular locations:  $K = 181$
  - $\sigma_0^2 = 4.642 \times 10^{-1}$
  - Number of snapshots:  $W = 20$
- Simulation
  - Number of independent realizations  $Q = 150$  (the noise and the signal amplitudes are random, while the DoAs are fixed)

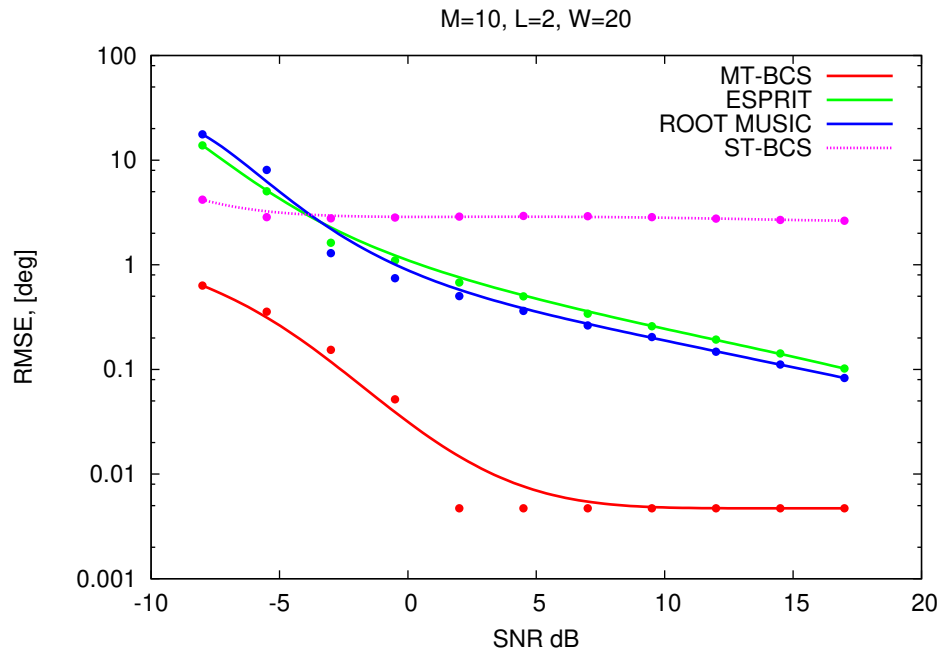


Figure 2: *RMSE* vs the *SNR*.

## Analysis vs $\Delta\theta^{(l+1)}$

### Simulation Parameters

- Scenario
  - BPSK signals ( $E_l^{inc} \in \{-1, 1\}$ )
  - Number of incident signals:  $L = 2$
  - **Signals spacing:**  $\Delta\theta^{(l+1)} \in [2, 20]$  *deg*
  - **Signals directions:**  $\underline{\theta} = \left\{ -\frac{\Delta\theta^{(l+1)}}{2}, \frac{\Delta\theta^{(l+1)}}{2} \right\}$  [*deg*]
  - Signal to noise ratio:  $SNR = 7$  *dB* (equivalent to a  $SNR = 4$  *dB* if the literature's definition is taken into account)
- Array parameters
  - Elements spacing:
  - Number of elements:  $M = 10$
- MT-BCS parameters
  - Number of angular locations:  $K = 181$
  - $a = 3.162$
  - $b = 3.981 \times 10^1$
- BCS parameters
  - Number of angular locations:  $K = 181$
  - $\sigma_0^2 = 4.642 \times 10^{-1}$
  - Number of snapshots:  $W = 20$
- Simulation
  - Number of independent realizations  $Q = 150$  (the noise and the signal amplitudes are random, while the DoAs are fixed)

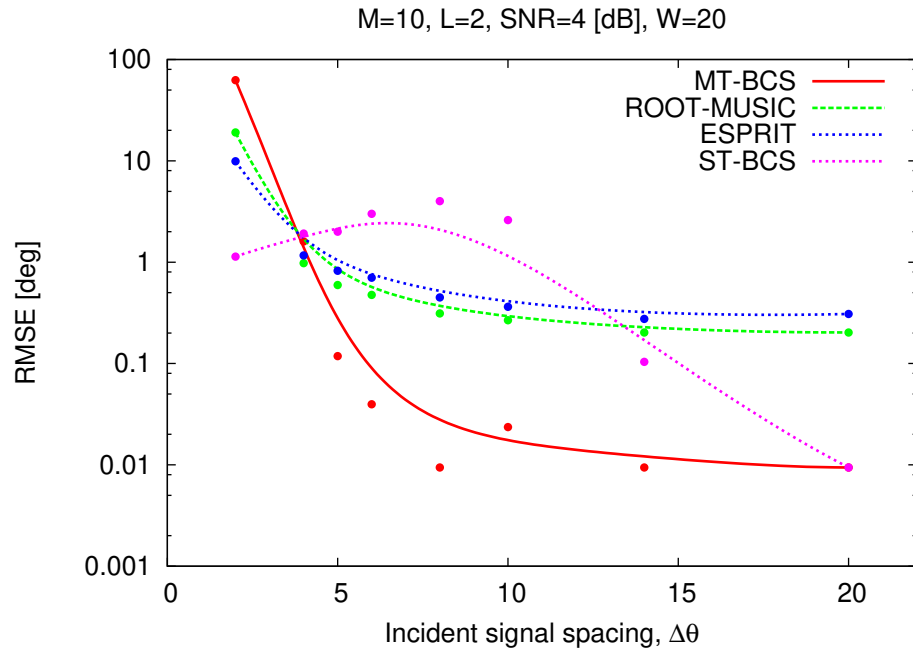


Figure 3:  $RMSE$  vs the signal spacing  $\Delta\theta^{(l+1)}$ .

## MT-BCS vs ST-BCS comparison: estimation examples

### Simulation Parameters

- Scenario
  - BPSK signals ( $E_l^{inc} \in \{-1, 1\}$ )
  - **Number of incident signals:**  $L \in [1, 9]$
  - **Signal directions:**

$L$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\theta_5$	$\theta_6$	$\theta_7$	$\theta_8$	$\theta_9$
1	0	-	-	-	-	-	-	-	-
2	0	7	-	-	-	-	-	-	-
4	0	7	35		-	-	-	-	-
6	0	7	35	-20	22	-37	-	-	-
8	0	7	35	-20	22	-37	-9	-67	-
9	0	7	35	-20	22	-37	-9	-67	54

Table 1: Signal directions for different numbers of signals.

- Signal to noise ratio:  $SNR = 7 \text{ dB}$
- Array parameters
  - Elements spacing:  $d = 0.5\lambda$
  - Number of elements:  $M = 10$
- $ST - BCS$  and  $MT - BCS$  parameters
  - Number of angular locations:  $K = 181$
  - Number of snapshots:  $W = 20$



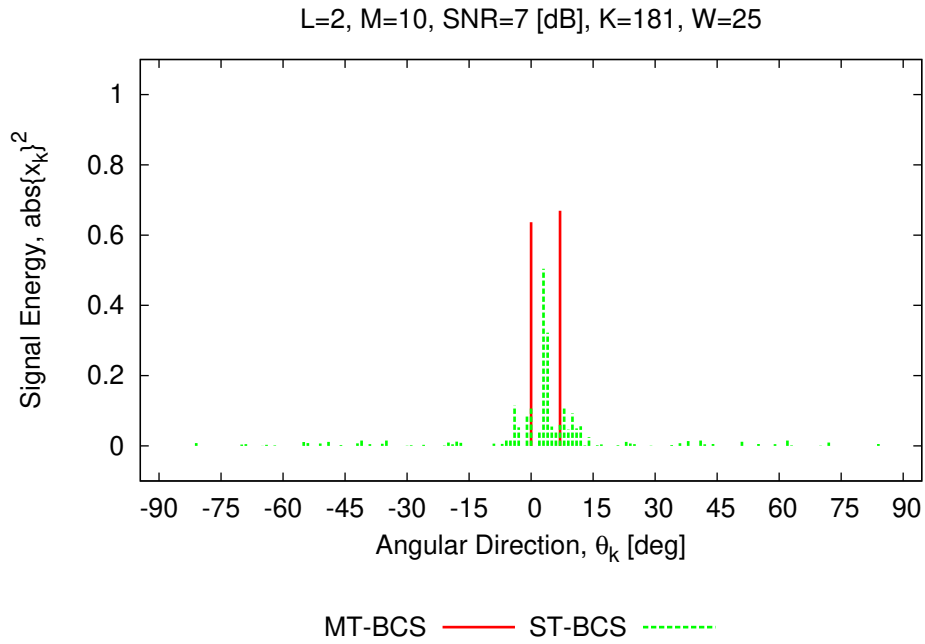


Figure 4: *MT-BCS* vs *ST-BCS*: esstimated signal amplitudes when  $L = 2$  signals impinging on the array. The number of snapshots is  $W = 25$ .

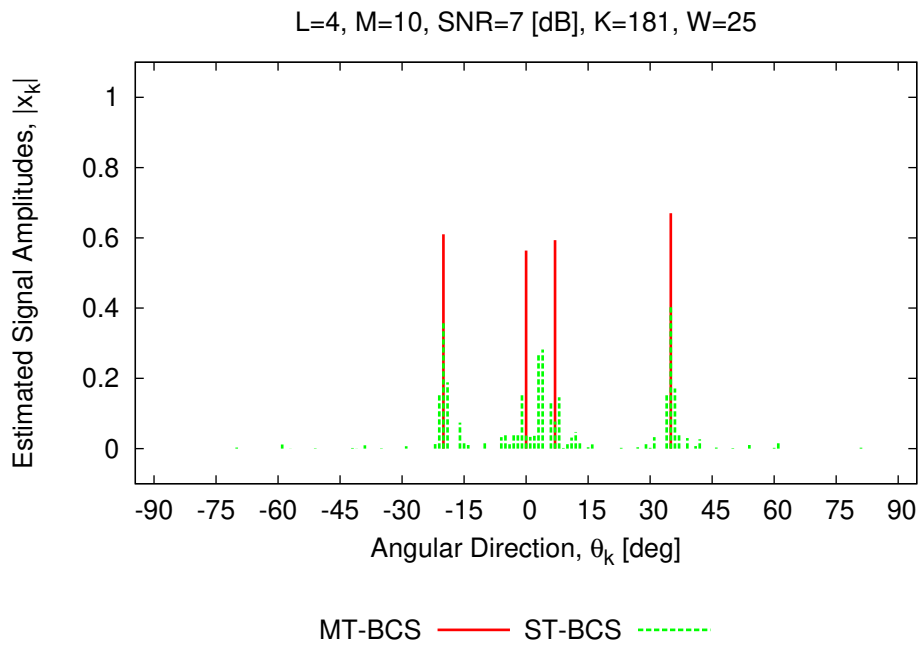


Figure 5: *MT-BCS* vs *ST-BCS*: esstimated signal amplitudes when  $L = 4$  signals impinging on the array. The number of snapshots is  $W = 25$ .

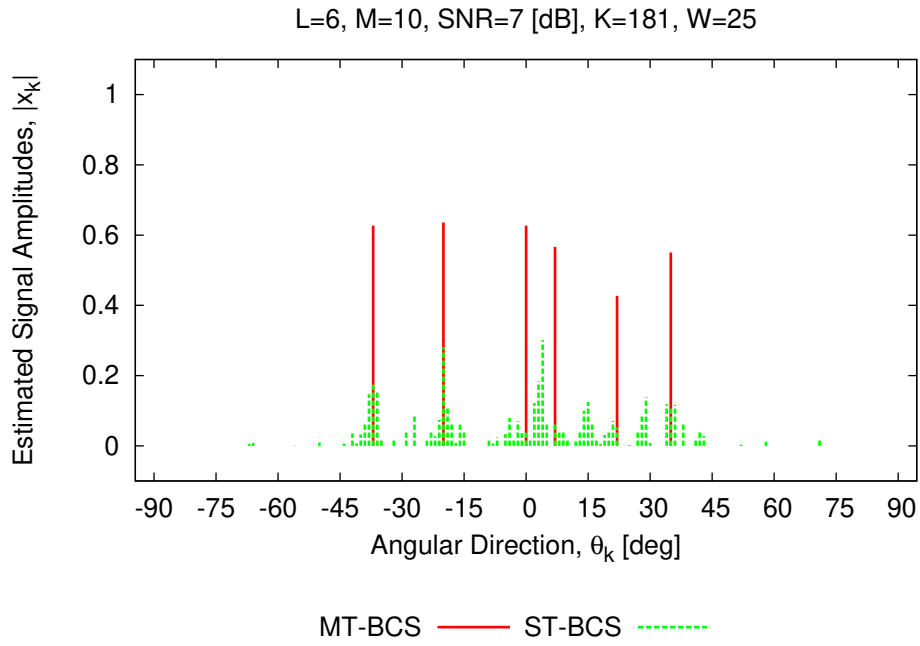


Figure 6: *MT-BCS* vs *ST-BCS*: esstimed signal amplitudes when  $L = 6$  signals impinging on the array. The number of snapshots is  $W = 25$ .

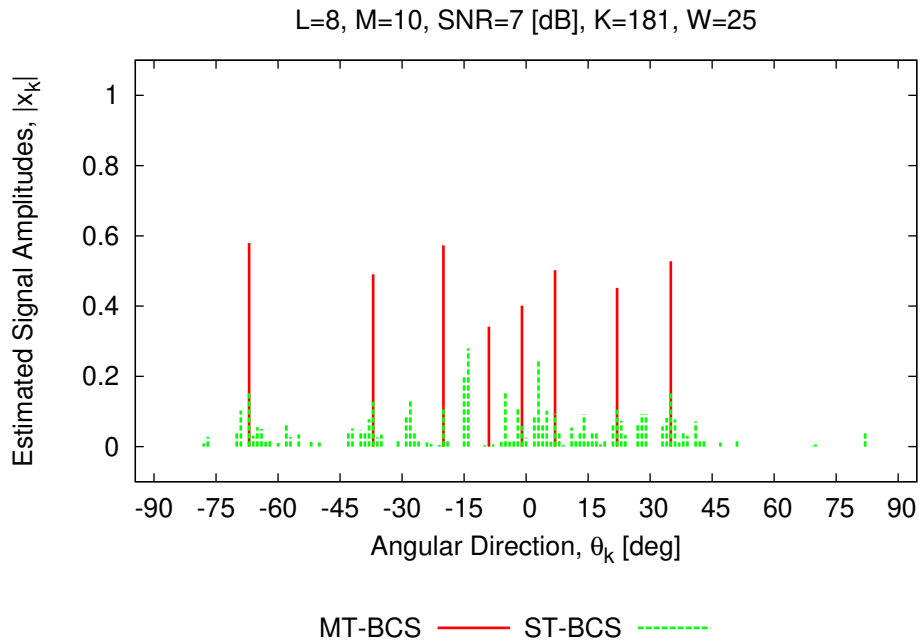


Figure 7: *MT-BCS* vs *ST-BCS*: esstimed signal amplitudes when  $L = 8$  signals impinging on the array. The number of snapshots is  $W = 25$ .

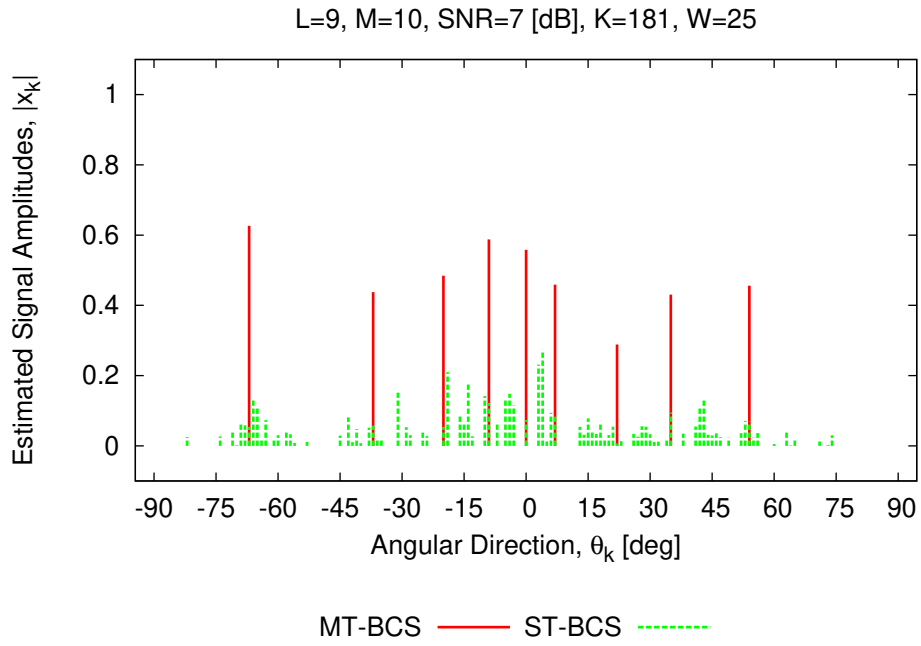


Figure 8: *MT-BCS* vs *ST-BCS*: esstimated signal amplitudes when  $L = 9$  signals impinging on the array. The number of snapshots is  $W = 25$ .

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More information on the topics of this document can be found in the following list of references.

## References

- [1] M. Carlin, P. Rocca, G. Oliveri, F. Viani, and A. Massa, "Directions-of-arrival estimation through Bayesian Compressive Sensing strategies," *IEEE Trans. Antennas Propag.*, vol. 61, no. 7, pp. 3828-3838, Jul. 2013 (DOI: 10.1109/TAP.2013.2256093).
  - [2] M. Carlin, P. Rocca, G. Oliveri, and A. Massa, "Bayesian compressive sensing as applied to directions-of-arrival estimation in planar arrays," *J. Electr. Comput. Eng. - Special Issue on "Advances in Radar Technologies"*, vol. 2013, pp. 1-12, 2013 (DOI: 10.1155/2013/245867).
  - [3] M. Carlin, P. Rocca, "A Bayesian compressive sensing strategy for direction-of-arrival estimation," *2012 6th European Conference on Antennas and Propagation (EUCAP)*, Prague, Czech Republic, 26-30 March, 2012, pp. 1508-1509 (DOI: 10.1109/EuCAP.2012.6206667).
  - [4] L. Lizzi, F. Viani, M. Benedetti, P. Rocca, and A. Massa, "The M-DSO-ESPRIT method for maximum likelihood DoA estimation," *Progress in Electromagnetic Research*, vol. 80, pp. 477-497, 2008 (DOI: 10.2528/PIER07121106).
  - [5] M. Donelli, F. Viani, P. Rocca, and A. Massa, "An innovative multi-resolution approach for DoA estimation based on a support vector classification," *IEEE Trans. Antennas Propag.*, vol. 57, no. 8, pp. 2279-2292, Aug. 2009 (DOI: 10.1109/TAP.2009.2024485).
  - [6] L. Lizzi, G. Oliveri, P. Rocca, and A. Massa, "Estimation of the direction-of-arrival of correlated signals by means of a SVM-based multi-resolution approach," *2010 IEEE Antennas and Propagation Society International Symposium*, Toronto, ON, Canada, 2010, pp. 1-4, (DOI: 10.1109/APS.2010.5560955).
  - [7] A. Massa, P. Rocca, and G. Oliveri, "Compressive sensing in electromagnetics - A review," *IEEE Antennas Propag. Mag.*, pp. 224-238, vol. 57, no. 1, Feb. 2015 (DOI: 10.1109/MAP.2015.2397092).
  - [8] G. Oliveri and A. Massa, "Bayesian compressive sampling for pattern synthesis with maximally sparse non-uniform linear arrays," *IEEE Trans. Antennas Propag.*, vol. 59, no. 2, pp. 467-481, Feb. 2011 (DOI: 10.1109/TAP.2010.2096400).
  - [9] G. Oliveri, M. Carlin, and A. Massa, "Complex-weight sparse linear array synthesis by Bayesian Compressive Sampling," *IEEE Trans. Antennas Propag.*, vol. 60, no. 5, pp. 2309-2326, May 2012 (DOI: 10.1109/TAP.2012.2189742).
  - [10] G. Oliveri, P. Rocca, and A. Massa, "Reliable diagnosis of large linear arrays - A Bayesian Compressive Sensing approach," *IEEE Trans. Antennas Propag.*, vol. 60, no. 10, pp. 4627-4636, Oct. 2012 (DOI: 10.1109/TAP.2012.2207344).
  - [11] F. Viani, G. Oliveri, and A. Massa, "Compressive sensing pattern matching techniques for synthesizing planar sparse arrays," *IEEE Trans. Antennas Propag.*, vol. 61, no. 9, pp. 4577-4587, Sept. 2013 (DOI: 10.1109/TAP.2013.2267195).
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- [12] G. Oliveri, E. T. Bekele, F. Robol, and A. Massa, "Sparsening conformal arrays through a versatile BCS-based method," *IEEE Trans. Antennas Propag.*, vol. 62, no. 4, pp. 1681-1689, Apr. 2014 (DOI: 10.1109/TAP.2013.2287894).
- [13] M. Carlin, G. Oliveri, and A. Massa, "Hybrid BCS-deterministic approach for sparse concentric ring isophoric arrays," *IEEE Trans. Antennas Propag.*, vol. 63, no. 1, pp. 378-383, Jan. 2015 (DOI: 10.1109/TAP.2014.2364306).
- [14] L. Poli, G. Oliveri, P.-P. Ding, T. Moriyama, and A. Massa, "Multifrequency Bayesian Compressive Sensing methods for microwave imaging," *J. Opt. Soc. Am. A*, vol. 31, no. 11, pp. 2415-2428, 2014 (DOI: 10.1364/JOSAA.31.002415).
- [15] G. Oliveri, N. Anselmi, and A. Massa, "Compressive sensing imaging of non-sparse 2D scatterers by a total-variation approach within the Born approximation," *IEEE Trans. Antennas Propag.*, vol. 62, no. 10, pp. 5157-5170, Oct. 2014 (DOI: 10.1109/TAP.2014.2344673).
- [16] L. Poli, G. Oliveri, and A. Massa, "Imaging sparse metallic cylinders through a local shape function Bayesian Compressive Sensing approach," *J. Opt. Soc. Am. A*, vol. 30, no. 6, pp. 1261-1272, 2013 (DOI: 10.1364/JOSAA.30.001261).
- [17] F. Viani, L. Poli, G. Oliveri, F. Robol, and A. Massa, "Sparse scatterers imaging through approximated multi-task compressive sensing strategies," *Microw. Opt. Technol. Lett.*, vol. 55, no. 7, pp. 1553-1558, Jul. 2013 (DOI: 10.1002/mop.27612).
- [18] L. Poli, G. Oliveri, P. Rocca, and A. Massa, "Bayesian compressive sensing approaches for the reconstruction of two-dimensional sparse scatterers under TE illumination," *IEEE Trans. Geosci. Remote Sens.*, vol. 51, no. 5, pp. 2920-2936, May 2013 (DOI: 10.1109/TGRS.2012.2218613).
- [19] L. Poli, G. Oliveri, and A. Massa, "Microwave imaging within the first-order Born approximation by means of the contrast-field Bayesian compressive sensing," *IEEE Trans. Antennas Propag.*, vol. 60, no. 6, pp. 2865-2879, Jun. 2012 (DOI: 10.1109/TAP.2012.2194676).
- [20] G. Oliveri, P. Rocca, and A. Massa, "A Bayesian Compressive sampling-based inversion for imaging sparse scatterers," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 10, pp. 3993-4006, Oct. 2011 (DOI: 10.1109/TGRS.2011.2128329).
- [21] G. Oliveri, L. Poli, P. Rocca, and A. Massa, "Bayesian compressive optical imaging within the Rytov approximation," *Opt. Lett.*, vol. 37, no. 10, pp. 1760-1762, 2012 (DOI: 10.1364/OL.37.001760).
- [22] L. Poli, G. Oliveri, F. Viani, and A. Massa, "MT-BCS-based microwave imaging approach through minimum-norm current expansion," *IEEE Trans. Antennas Propag.*, vol. 61, no. 9, pp. 4722-4732, Sep. 2013 (DOI: 10.1109/TAP.2013.2265254).
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