COMPARISON OF VARIOUS DETECTION SCHEMES FOR STAP RADAR BASED ON EXPERIMENTAL DATA.

G. Pailloux[1], *F. Pascal*[2], *J.P. Ovarlez*[1,2] *and P. Forster*[3]

[1] ONERA - DEMR/TSI, Chemin de la Hunière, F-91120 Palaiseau, France
[2] SONDRA-Supélec Laboratory, Plateau du Moulon, 3 rue Joliot Curie, 91192 Gif-sur-Yvette Cedex, France
[3] SATIE, CNRS, ENS Cachan, UniverSud, 61, av President Wilson, F-94230 Cachan, France

e-mail: guilhem.pailloux@onera.fr, frederic.pascal@supelec.fr, jean-philippe.ovarlez@onera.fr, philippe.forster@u-paris10.fr

ABSTRACT

In the general area of radar detection, several detection schemes have been developed for the two last decades. These detectors may be classified into two major families: Gaussian and non-Gaussian detectors, depending on the clutter assumptions. Moreover, methods have been proposed to take into account the structure of the Clutter Covariance Matrix (CCM) in order to improve its estimation accuracy. In a STAP (Space Time Adaptive Processing) context, this paper compares four Gaussian and non-Gaussian detection schemes on experimental data. The obtained results clearly demonstrate the improved detection performance brought by a recently proposed persymmetric non-Gaussian detector.

***Index Terms*—** Adaptive signal detection, Covariance matrices, Radar clutter, Radar detection, Radar data processing.

1. INTRODUCTION

Conventional radars perform separate processing in the spatial and time domains. STAP radars, by jointly processing spatial and time data, achieve a better clutter rejection and therefore an improved detection of targets. The radar under consideration in this paper is a coherent pulsed-Doppler radar with a N-elements Uniformly spaced Linear Array (ULA). This radar transmits bursts of M pulses, and L range samples are collected over each pulse repetition interval [1]. In this context, the basic problem of detecting a known signal $\mathbf{s} = A\mathbf{p} \in \mathbb{C}^{MN}$ corrupted by an additive clutter $\mathbf{c}$, in a range bin under test, can be stated as the following binary hypothesis test:

$$\begin{cases} H_0 : \mathbf{y} = \mathbf{c}, & \mathbf{y}_k = \mathbf{c}_k, \text{ for } 1 \le k \le K\,, \\ H_1 : \mathbf{y} = A\,\mathbf{p} + \mathbf{c}, & \mathbf{y}_k = \mathbf{c}_k, \text{ for } 1 \le k \le K\,, \end{cases} \quad (1)$$

where $\mathbf{y}$ is the complex $MN \times 1$ snapshot of the received space-time data, A is an unknown complex target amplitude, and $\mathbf{p}$ is a known steering vector. In sidelooking STAP, the steering vector $\mathbf{p}$ is the Kronecker product (denoted $\otimes$) of a $M \times 1$ temporal steering vector $\mathbf{b}(f)$ depending on the doppler shift and a $N \times 1$ spatial steering vector $\mathbf{a}(\theta)$ depending on the target direction:

$$\mathbf{p}(f, \theta) = \mathbf{b}(f) \otimes \mathbf{a}(\theta). \quad (2)$$

Under both hypotheses in problem (1), it is assumed that K signal-free data $\mathbf{y}_k$ are available for clutter parameters estimation. The $\mathbf{y}_k$'s are the so-called secondary data. In the STAP theoretical framework, they are assumed independent and identically distributed with the same distribution as $\mathbf{c}$.

The development of detectors is based on assumptions on the clutter statistic. Moreover, the adaptive version of these detectors requires an estimation of the CCM. Various solutions to these problems have been proposed in the literature. The purpose of this paper is to compare some of them on experimental data.

The paper is organized as follows. Section (2) presents the studied detection schemes and section (3) compares these detectors on experimental STAP data.

In the sequel, ^{H} denotes the transpose conjugate, * the conjugate and $^\top$ the transpose operator, $\mathbf{I}_N$ is the N-th order identity matrix, $\mathbf{M}$ denotes the CCM and $\widehat{\mathbf{M}}$ an estimate of $\mathbf{M}$ based on secondary data.

2. STUDIED DETECTION SCHEMES

Two types of detectors will be investigated: the Adaptive Matched Filter (AMF) based on Gaussian assumption for the clutter [2], and the Adaptive Normalized Matched Filter (ANMF) for non-Gaussian clutter [3] also referred to as GLRT-LQ [4] and ACE [5]. The corresponding detection tests are:

$$\Lambda_{AMF} = \frac{|\mathbf{p}^H \widehat{\mathbf{M}}^{-1} \mathbf{y}|^2}{\mathbf{p}^H \widehat{\mathbf{M}}^{-1} \mathbf{p}} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda\,, \quad (3)$$

Authors would like to thank the DGA/CELAR, 35170 Bruz, France, for the analysis of their data.

$$\Lambda_{ANMF} = \frac{|\mathbf{p}^H \widehat{\mathbf{M}}^{-1} \mathbf{y}|^2}{(\mathbf{p}^H \widehat{\mathbf{M}}^{-1} \mathbf{p})(\mathbf{y}^H \widehat{\mathbf{M}}^{-1} \mathbf{y})} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda' , \tag{4}$$

where λ and λ' are the appropriate detection thresholds to reach a given Probability of False Alarm.
In the Gaussian case, the widely used estimate in (3) for the CCM is the Sample Covariance Matrix (SCM) built from the secondary data and denoted by:

$$\widehat{\mathbf{M}}_{SCM} = \frac{1}{K} \sum_{k=1}^{K} \mathbf{y}_k \, \mathbf{y}_k^H . \tag{5}$$

The resulting detection test will be called the AMF-SCM.

In the non Gaussian case, Conte and Gini in [6, 7] have shown that a maximum likelihood estimate $\widehat{\mathbf{M}}$ of $\mathbf{M}$, which will be called the Fixed Point (FP) estimate $\widehat{\mathbf{M}}_{FP}$, is a solution of the following equation:

$$\widehat{\mathbf{M}} = \frac{m}{K} \sum_{k=1}^{K} \left(\frac{\mathbf{y}_k \, \mathbf{y}_k^H}{\mathbf{y}_k^H \, \widehat{\mathbf{M}}^{-1} \, \mathbf{y}_k} \right) . \tag{6}$$

Existence and uniqueness of the above equation solution $\widehat{\mathbf{M}}_{FP}$ have been investigated in [8], and its statistical properties have been studied in [9]. The resulting detection test will be called the ANMF-FP.

It is clear that the estimation accuracy of $\widehat{\mathbf{M}}$ has an important impact on detection performance. In our STAP context, with an ULA, the CCM $\mathbf{M}$ has the persymmetric structure [10]: $\mathbf{M} = \mathbf{J}_{MN} \, \mathbf{M}^* \, \mathbf{J}_{MN}$, where $\mathbf{J}_{MN}$ is the MN-dimensional antidiagonal matrix having 1 as non-zero elements. The signal vector is also persymmetric, i.e. it satisfies $\mathbf{p} = \mathbf{J}_{MN} \, \mathbf{p}^*$.

Following the pioneer work of Nitzberg [11] and Cai [12], we proposed in [13] and [14] two detectors called respectively Persymmetric AMF (PAMF) and Persymmetric FP (PFP) to exploit the persymmetric structure for estimating the CCM. Let $\mathbf{T}$ be the unitary matrix defined as:

$$\mathbf{T} = \begin{cases} \frac{1}{\sqrt{2}} \begin{pmatrix} \mathbf{I}_{MN/2} & \mathbf{J}_{MN/2} \\ i \, \mathbf{I}_{MN/2} & -i \, \mathbf{J}_{MN/2} \end{pmatrix} \\ \\ \frac{1}{\sqrt{2}} \begin{pmatrix} \mathbf{I}_{(MN-1)/2} & \mathbf{0} & \mathbf{J}_{(MN-1)/2} \\ \mathbf{0} & \sqrt{2} & \mathbf{0} \\ i \, \mathbf{I}_{(MN-1)/2} & \mathbf{0} & -i \, \mathbf{J}_{(MN-1)/2} \end{pmatrix} \end{cases} \tag{7}$$

respectively for MN even and odd. The resulting detection schemes are:

$$\Lambda_{PAMF} = \frac{|\mathbf{p}^H \mathbf{T}^H [\mathcal{R}e(\mathbf{T} \widehat{\mathbf{M}}_{SCM} \mathbf{T}^H)]^{-1} \mathbf{T} \mathbf{y}|^2}{\mathbf{p}^H \mathbf{T}^H [\mathcal{R}e(\mathbf{T} \widehat{\mathbf{M}}_{SCM} \mathbf{T}^H)]^{-1} \mathbf{T} \mathbf{p}} , \tag{8}$$

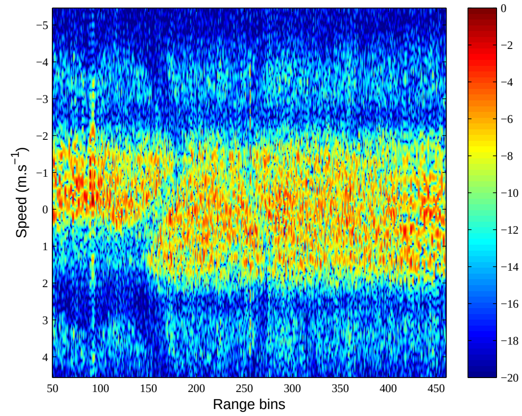

Fig. 1. Range-Doppler clutter data

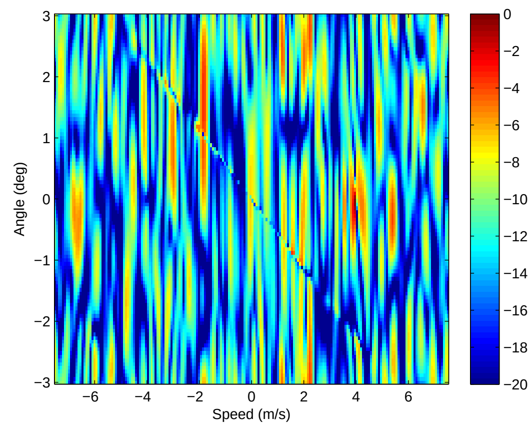

Fig. 2. AMF-SCM detection results for the range bin 215.

$$\Lambda_{PFP} = \frac{|\mathbf{p}^H \mathbf{T}^H [\mathcal{R}e(\mathbf{T} \widehat{\mathbf{M}}_{FP} \mathbf{T}^H)]^{-1} \mathbf{T} \mathbf{y}|^2}{(\mathbf{p}^H \mathbf{T}^H [\mathcal{R}e(\mathbf{T} \widehat{\mathbf{M}}_{FP} \mathbf{T}^H)]^{-1} \mathbf{T} \mathbf{p})(\mathbf{y}^H \mathbf{T}^H [\mathcal{R}e(\mathbf{T} \widehat{\mathbf{M}}_{FP} \mathbf{T}^H)]^{-1} \mathbf{T} \mathbf{y})} . \tag{9}$$

This method allows to virtually double the number of secondary data [13, 14]. This is an interesting property in STAP where few secondary data are available and where conventional detectors performance is limited by the well-known RMB's rule [15]: $K > 2NM$ for less than 3 dB detection loss.

3. COMPARISON ON EXPERIMENTAL DATA

The STAP data are provided by the DGA/CELAR's simulator that allows to synthetize, in side looking configuration, STAP datacubes from very high resolution Synthetic Aperture Radar (SAR). The number of ULA sensors is $N = 4$ and the number of coherent pulses can be up to $M = 64$. The center frequency and the bandwidth are respectively equal to

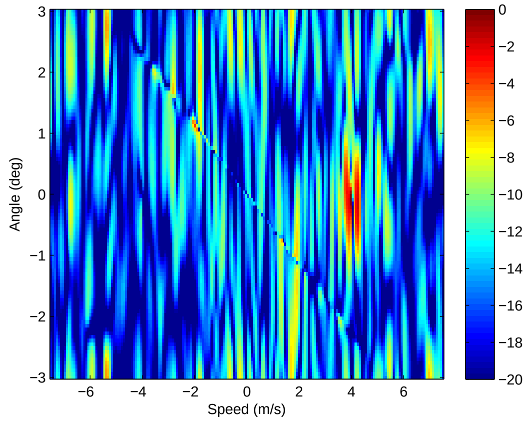

Fig. 3. PAMF detection results for the range bin 215.

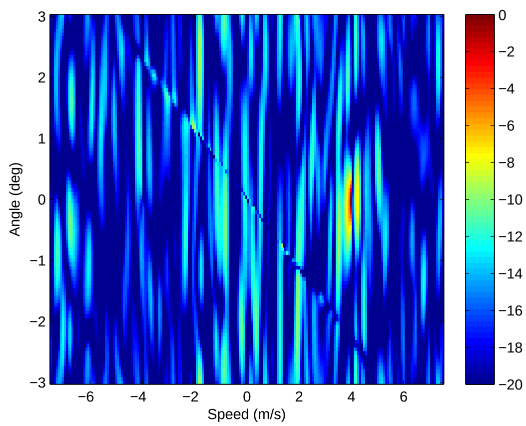

Fig. 4. ANMF-FP detection results for the range bin 215.

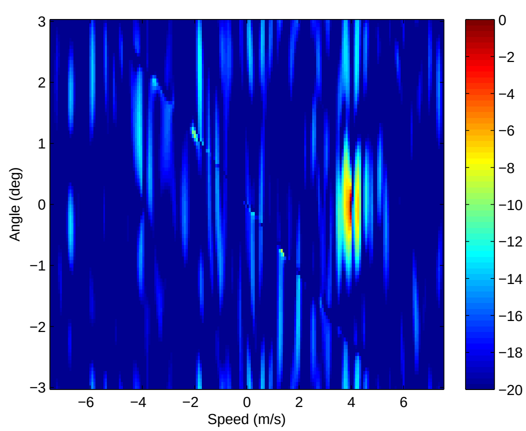

Fig. 5. PFP detection results for the range bin 215.

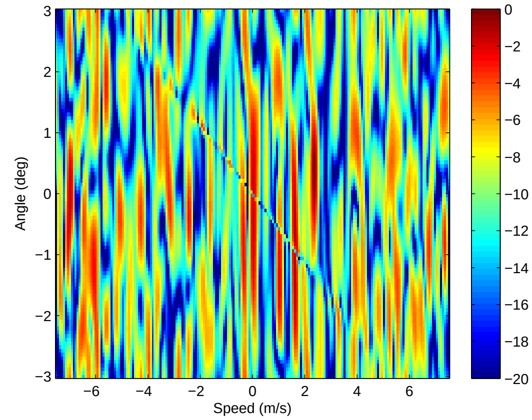

Fig. 6. AMF-SCM detection results for 10 targets with different speeds and located in range bin 256.

$f_0 = 10$ GHz and $B = 5$ MHz. The radar velocity is given by $V = 100$ m/s. The inter-element spacing is $d = 0.3$ m and the pulse repetition frequency is $f_r = 1$ kHz. The number of secondary data used to estimate the CCM is here $K = 410$ for all the presented results.

Figure 1 presents a clutter map obtained for sensor 1. In the first studied case, a single target is at range bin 216 with a speed of 4 m/s and azimuth 0. Figure 2 and 3 display respectively the test statistics of the two Gaussian detectors AMF-SCM and PAMF. As expected, the PAMF outperforms the AMF-SCM. Indeed, Brennan's rule is not satisfied by the AMF-SCM, while the virtual doubling of secondary data brought by the PAMF allows to satisfy this rule: $NM = 256 < K = 410 < 2NM = 512$. Figure 4 and 5 display the test statistics of the non-Gaussian detectors: the ANMF-FP and the PFP. The same conclusion holds for these detectors. Concerning the clutter model exploited by these detectors, it is clear that these non-Gaussian detectors lead to a spectacular improvement in terms of clutter rejection compared to the Gaussian detectors.

The second set of data contains 10 targets at the range bin 255, with speeds from -4 m/s to 4 m/s. Figures 6, 7, 8 and 9 refer respectively to AMF-SCM, PAMF, ANMF-FP and PFP. Firstly, it may be noted that the AMF-SCM yields very poor results. Secondly, the best result is again provided by the PFP which takes into account the non-Gaussianity of the clutter and the persymmetry of the CCM.

4. CONCLUSION

The experimental data exploited in this paper lead to two main results. Firstly, non-Gaussian detectors based on the ANMF and the Fixed-Point CCM estimate, outperform conventional Gaussian detectors based on the AMF and the SCM. Secondly, exploiting the persymmetric structure of the CCM yields an additional improvement in terms of detection. These conclusions make the PFP an interesting detector for STAP radars.

5. REFERENCES

[1] J. Ward, "Space-Time Adaptive Processing for Airborne Radar," *tech. rep.*, vol. Lexington, Massachusetts, USA, December 1994.

[2] F.C. Robey, D.R. Fuhrmann, E.J. Kelly, and R. Nitzberg, "A CFAR Adaptive Matched Filter Detector," *IEEE Trans. on AES*, vol. 23, pp. 208–216, January 1992.

[3] E. Conte, M. Lops, and G. Ricci, "Adaptive Radar Detection in Coumpound Radar Clutter," *Proceedings of the EUSIPCO*, pp. 526–529, September 1994.

[4] F. Gini, "Sub-Optimum Coherent Radar Detection in a Mixture of K-Distributed and Gaussian Clutter," *IEE Proc. on Radar, Sonar Navig.*, vol. 144, pp. 39–48, February 1997.

[5] L.L. Scharf and L.T. McWhorter, "Adaptive Matched Subspace Detectors and Adaptive Coherence Estimators," *Proceedings of the 30th Asilomar Conference on Signals, Systems, and Computers*, vol. 2, pp. 1114–1117, November 1996.

[6] F. Gini and M. V Greco, "Covariance matrix estimation for CFAR detection in correlated heavy tailed clutter," *Signal Processing, special section on Signal Processing with Heavy Tailed Distributions,*, vol. 82, pp. 1847–1859, December 2002.

[7] E. Conte, A. De Maio, and G. Ricci, "Recursive estimation of the covariance matrix of a compound-Gaussian process and its application to adaptive CFAR detection," *IEEE Trans. on SP*, vol. 50, pp. 1908–1915, August 2002.

[8] F. Pascal, Y. Chitour, J.P. Ovarlez, P. Forster, and P. Larzabal, "Covariance Structure Maximum Likelihood Estimates in Compound Gaussian Noise: Existence and Algorithm Analysis," *IEEE Trans. on SP*, vol. 56, pp. 34–38, January 2008.

[9] F. Pascal, P. Forster, J.P. Ovarlez, and P. Larzabal, "Performance Analysis of Covariance Matrix Estimate in Impulsive Noise," *IEEE Trans. on SP*, pp. 2206–2217, June 2008.

[10] E. Conte and A. De Maio, "Exploiting Persymmetry for CFAR Detection in Compound-Gaussian Clutter," *IEEE Trans. on AES*, vol. 39, pp. 719–724, April 2003.

[11] R. Nitzberg and J.R. Burke, "Application of Maximum Likelihood Estimation of Persymmetric Covariance Matrices to Adaptive Detection," *IEEE Trans. on AES*, vol. 25, pp. 124–127, January 1980.

[12] L. Cai and H. Wang, "A Persymmetric Multiband GLR Algorithm," *IEEE Trans. on AES*, pp. 806–816, July 1992.

[13] G. Pailloux, P. Forster, J.P. Ovarlez, and F. Pascal, "On Persymmetric Covariance Matrices in Adaptive Detection," *IEEE ICASSP 2008*, pp. 2305–2308, April 2008.

[14] G. Pailloux, J.P. Ovarlez, F. Pascal, and P. Forster, "A SIRV-CFAR Adaptive Detector Exploiting Persymmetric Clutter Covariance Structure," *IEEE RadarConf 2008*, pp. 1139–1144, May 2008.

[15] I.S. Reed, J.D. Mallett, and L.E. Brennan, "Rapid Convergence Rate in Adaptive Arrays," *IEEE Trans. on AES*, vol. 10, pp. 853–863, November 1974.

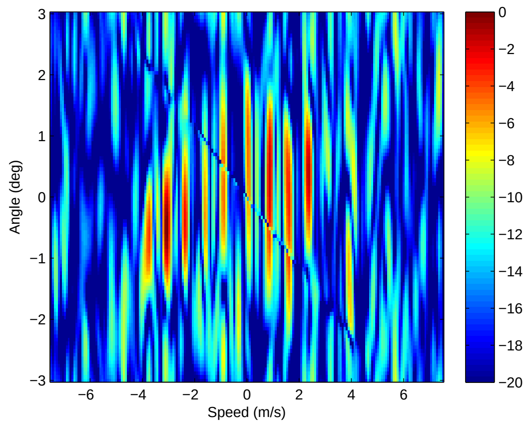

Fig. 7. PAMF detection results for 10 targets with different speeds and located in range bin 256.

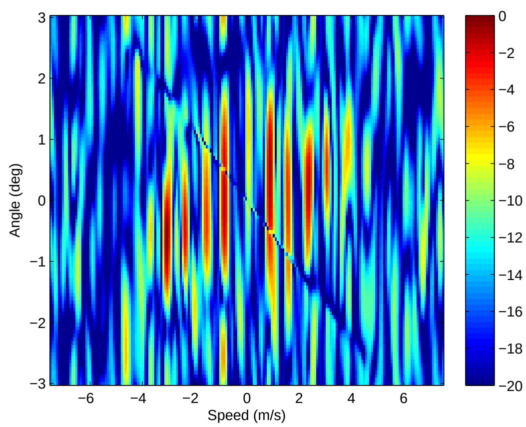

Fig. 8. ANMF-FP detection results for 10 targets with different speeds and located in range bin 256.

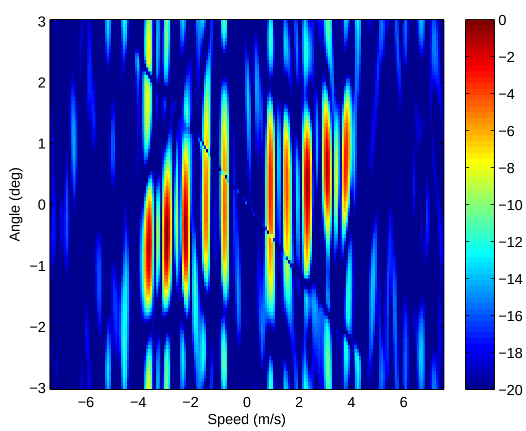

Fig. 9. PFP detection results for 10 targets with different speeds and located in range bin 256.