# Satellite Adaptive Onboard Beamforming Using Neuromorphic Processors

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Abstract—The demand for improved satellite communication (SatCom)-based broadband connectivity has led to significant technological advancements, particularly in non-geostationary orbit (NGSO) satellites. The new SatCom systems are expected to have flexible beam footprints with fully adaptable payloads while being energy-efficient. With this in mind, this paper explores using neuromorphic processors (NPs) for the in-orbit receive digital beamforming design. We specifically address the beamsteering challenges of high-speed user mobility by means of beamforming adaptation. Inspired by thinned antenna arrays, the proposed beamforming solutions are based on the least absolute shrinkage and selection operator (LASSO) and are adapted to NPs using spiking locally competitive algorithms, namely S-LCA and S-LCA with graded spikes. The proposed approaches can benefit from the energy efficiency of NPs and further reduce the SatCom payload's power consumption by turning off as many radio frequency chains as possible without compromising the beamforming performance. Numerical experiments conducted on a real-world aeronautical dataset demonstrate that the proposed NP-oriented solutions offer performance on par with conventional optimization algorithms, with the promise of a lower energy expenditure after future implementation on dedicated hardware.

Index Terms—Beamforming, LASSO, Neuromorphic Processor, Non-geostationary Orbit, Satellite Communications, Sparsity

# I. INTRODUCTION

Satellite communication (SatCom) systems have entered a new era, bridging the coverage gap of current terrestrial mobile services [1] and driving the evolving space economy [2]. The latest SatCom developments include lower orbital deployments and in-orbit reconfigurability of satellite-payload resources. New non-geostationary orbit (NGSO) communication satellites are equipped with fully reconfigurable payloads that can quickly adapt to changes in traffic demand and channel conditions [3]. In this context, beamforming plays a key role.

Beamforming is a mature spatial signal processing technique that can be implemented using different architectures, such as digital beamforming (DBF) [4], digitally-controlled phase-shifter-based beamforming [5], and hybrid beamforming [6]. Moreover, different design strategies can be targeted, such as fixed beamforming [7], where the coverage of areas of interest is ensured by generating beams of fixed size and shape, and dynamic (or adaptive) beamforming [8], where the design is adapted according to users' traffic demand and/or relative mobility between ground/space-segment nodes.

DBF techniques offer several advantages over conventional analog (or hybrid) beamforming in various applications. In DBF, a signal processor controls the excitation of the antenna array elements (or subarrays) to synthesize the desired radiation pattern in the case of transmit beamforming. Conversely, the signal processor can also control the combination of the digitized signals coming from the radio frequency chains (RFCs) associated with each antenna element (or each subarray) in order to spatially filter the impinging signal in the so-called receive beamforming [9]. The overall objective is to increase the gain in the direction of the intended receivers or desired signal sources, while reducing the gain from unwanted steering angles or potential interference sources [10].

An overview of the trade-offs between conventional SatCom beamforming and DBF strategies in the context of mobile SatCom applications is provided in [11]. DBF enables adaptive beamforming and is essential for meeting the demands of modern heterogeneous traffic patterns in mobile SatCom. Efficient stream-like/online solutions are required to design and realize onboard beamforming due to evolving beam patterns as a spatiotemporal function of data traffic.

A crucial metric related to onboard processing in SatCom payloads is energy efficiency. In this context, neuromorphic processors (NPs) are promising hardware solutions. Unlike conventional von Neumann computers, NPs operate using binary *spikes*, offer more parallelization, and minimize the separation of processing and memory [12]. NPs are well known for their event-driven operation mode [13], which offers interesting characteristics for reconfigurable systems such as the SatCom beamforming application considered in this work. NPs have been demonstrated to provide significant energy savings and low-latency, both of which are attractive qualities for in-orbit applications. The usage of such devices has already

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been the focus of research from both the National Aeronautics and Space Administration (NASA) [14] and the European Space Agency (ESA) [15].

# A. Main contributions

In this paper, we address the in-orbit receive DBF design using NPs for an NGSO system serving high-speed mobile platforms like aircraft in the uplink — see Fig. 1. In current commercial systems, beamforming calculations are commonly done on-ground, at the gateway (GW) side, after receiving the location information of the mobile platforms via returnlink signaling. However, by the time that the beamformer coefficients are calculated and sent to the satellite platform for realization, the actual users' location might be substantially different than that used to design the beamforming coefficients. Hence, we focus on designing adaptive onboard beamforming algorithms that can be readily deployed on energy-efficient NPs.<sup>1</sup>

We first propose a formulation of the beamforming problem based on the least absolute shrinkage and selection operator (LASSO) [16], which serves as the basis for the NP-oriented solutions. Toward this, we consider a modified minimum variance distortionless response (MVDR) design [17] by enforcing sparsity on the beamforming coefficients. This is inspired by thinned antenna arrays (see, for instance, [18]), and our motivation for adopting such an approach is to turn off as many payload's RFCs as possible to decrease the underlying power consumption without compromising performance. As observed in [19], applying the original LASSO approach [16] in the context of complex-valued variables is not straightforward.

Building on the basic LASSO formulation, we propose to solve the DBF design problem using the spiking locally competitive algorithm (S-LCA) and the S-LCA with graded spikes (S-LCA-GS), which can be efficiently implemented on NPs. We evaluate these algorithms on an aeronautical dataset consisting of real-world time-varying airplane coordinates obtained from [20]. The algorithms are implemented using Intel's Lava simulator [21], i.e., the open-source software for neuro-inspired applications and baseline for Intel's secondgeneration neuromorphic research chip [22].

# B. Organization

The remainder of this paper is structured as follows. Section II describes the system model. Section III introduces the basic LASSO beamforming formulation, and Section IV describes the proposed adaptations for obtaining NP-oriented solutions. Section V reports the simulation results, and Section VI contains the concluding remarks.

# II. SYSTEM MODEL

We consider an NGSO satellite that offers service to highspeed mobile platforms such as aircraft. The NGSO satellite is assumed to be capable of generating several steerable beams over a given service area bounded by its field of view. In this



Fig. 1: Latitude/longitude map with the projection on Earth of the trajectories of an aircraft in red and an NGSO satellite in yellow. Other aircraft are depicted fixed (i.e., a single snapshot) in white. For further details, see Section V-A.

case, the direction of each central beam boresight is computed based on the target angle of transmission/reception. The main objective here is to design the receive DBF on the user uplink so that each mobile platform is assigned a single spot beam. The design should be updated following the fast mobility pattern of the user platform, considering also the NGSO satellite's mobility. Such a beamforming model is proposed as a baseline scenario in the 3rd Generation Partnership Project (3GPP) 5G solutions to support nonterrestrial networks [23].

The antenna architecture at the satellite is assumed to be a uniform planar array (UPA) of dimension  $N_{\text{UPA}} \times N_{\text{UPA}}$ , connected to  $N \leq N_{\text{UPA}}^2$  RFCs. Assume that the user terminal (UT) — an aircraft — is uploading a signal, whose baseband representation is s(t), in the presence of I baseband interfering signals  $s_i(t)$ ,  $i \in \{1, \dots, I\}$ . The  $N \times 1$  narrowband baseband received signal vector of the satellite's UPA can be written as

$$\boldsymbol{y}(t) = \underbrace{\boldsymbol{h}(t) \mathrm{e}^{\mathrm{j}\varepsilon_{\mathrm{D}}(t)} \boldsymbol{s}(t) \boldsymbol{a}(\boldsymbol{\theta}(t))}_{\mathrm{desired \ component}} + \underbrace{\sum_{i=1}^{I} \boldsymbol{h}_{i}(t) \mathrm{e}^{\mathrm{j}\varepsilon_{\mathrm{D},i}(t)} \boldsymbol{s}_{i}(t) \boldsymbol{a}(\boldsymbol{\theta}_{i}(t))}_{\mathrm{interference}} + \underbrace{\boldsymbol{n}(t)}_{\mathrm{noise}}, \tag{1}$$

where h(t) and  $h_i(t)$  are, respectively, the equivalent channel responses for the UT of interest and for I interferers;  $\varepsilon_D(t)$ and  $\varepsilon_{D,i}(t)$  are the carrier frequency offsets for the UT of interest and for the I interfering users, respectively, which depend on the oscillators' uncertainties and Doppler shifts; and  $\theta(t) = [\phi(t) \quad \theta(t)]^T$  and  $\theta_i(t) = [\phi_i(t) \quad \theta_i(t)]^T$  are the 2D angles-of-arrival for the UT of interest and for the interfering users, respectively, with  $\phi(t), \phi_i(t)$  denoting the corresponding azimuth angles, whereas  $\theta(t), \theta_i(t)$  are the elevation angles. The vector  $\boldsymbol{a}(\theta(t))$  denotes the steering vector associated with the 2D angle-of-arrival  $\theta(t)$  for the given UPA and already

<sup>&</sup>lt;sup>1</sup>The implementation of the proposed NP-oriented algorithms on an actual neuromorphic chipset is beyond the scope of this conference contribution.

accounts for the added processing (sum of signals) when subarrays are employed (the case in which  $N < N_{\rm UPA}^2$ ).

We assume that  $s(t), s_i(t), h(t), h_i(t)$ , and n(t) are realizations of independent random processes with zero mean (except for the channels) and powers  $\sigma_s^2, \sigma_{s,i}^2, P_h, P_{h,i}$ , and  $\sigma_n^2$ , respectively. Under this assumption, the received signal in (1) is a realization of a zero-mean multivariate random process with covariance matrix

$$\boldsymbol{R}(t) = \sigma_s^2 P_h \boldsymbol{a}(\boldsymbol{\theta}(t)) \boldsymbol{a}^{\mathrm{H}}(\boldsymbol{\theta}(t)) + \sum_{i=1}^{I} \sigma_{s,i}^2 P_{h,i} \boldsymbol{a}(\boldsymbol{\theta}_i(t)) \boldsymbol{a}^{\mathrm{H}}(\boldsymbol{\theta}_i(t)) + \sigma_n^2 \boldsymbol{I}_N.$$
(2)

An important challenge with fast-moving platforms is to obtain an accurate estimate of the angles-of-arrival  $\theta(t)$  and  $\theta_i(t)$ , which are needed to design an efficient DBF. The satellite system may have access to an outdated location of the aircraft, which may be obtained either from any global navigation satellite system (GNSS) or from information in previously decoded frames or from the GW. To denote the inaccurate angles-of-arrival estimation, we will employ the notation  $\hat{\theta}(t) = \left[\hat{\phi}(t) \ \hat{\theta}(t)\right]^{\mathrm{T}}$ . Similarly, we will use the notation  $\hat{R}(t)$  to denote the estimated covariance matrix of the array output.<sup>2</sup>

# III. LASSO BEAMFORMING DESIGN

The objective of the proposed in-orbit DBF is threefold: (*i*) to ensure that the center of the spot beam is steered toward the corresponding fast-moving platform; (*ii*) to minimize the noise and interference that is collected by the beamformer from other undesired angles-of-arrival; and (*iii*) to minimize the number of nonzero beamforming weights in an attempt to maximize the number of RFCs that can be turned off. Goals (*i*) and (*ii*) are addressed by the conventional MVDR beamforming [17] — see Section V-A; while goal (*iii*) aims to save the payload's power.

We propose to cast the DBF design as a LASSO optimization problem [16] to compute the corresponding beamforming vector  $\boldsymbol{w} \in \mathbb{C}^{N \times 1}$ . This is formulated as the minimization

$$\begin{array}{ll} \underset{\boldsymbol{w} \in \mathbb{C}^{N \times 1}}{\text{minimize}} & \boldsymbol{w}^{\mathrm{H}} \widehat{\boldsymbol{R}}(t) \boldsymbol{w} + \lambda \left( \| \Re \left\{ \boldsymbol{w} \right\} \|_{1} + \| \Im \left\{ \boldsymbol{w} \right\} \|_{1} \right) \\ \text{subject to} & \boldsymbol{w}^{\mathrm{H}} \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right) = 1 \,, \end{array}$$

$$(3)$$

where  $\lambda > 0$  and  $\|\cdot\|_1$  is the  $\ell_1$ -norm of a vector.

The objective function in (3) includes two terms. The first term accounts for the overall signal power that is captured by the beamforming design, which is minimized to reduce the contribution received from angles not corresponding to the target angle  $\hat{\theta}(t)$ . Note that this is enforced with the linear constraint in (3), which sets the beam center toward the desired  $\hat{\theta}(t)$ . The second term in the objective function in (3) aims at enforcing sparsity in the real and complex parts of the beamforming weights. The predefined parameter  $\lambda$  controls the degree of sparsity. The idea is to enforce a high degree of sparsity in the real and imaginary parts of w, i.e.,  $\Re \{w\}$  and  $\Im \{w\}$ , in order to enforce as many as possible complex-valued entries of w to be zeroed.

After solving the problem in (3), the coefficients are transformed so that those with negligible values are mapped to zero. There are different ways to do this, such as considering the coefficients that represent a certain percentage of the total energy of the beamforming vector.

#### **IV. PROPOSED NP-ORIENTED BEAMFORMING**

While problem (3) can be iteratively solved using convex optimization computational tools such as CVX, a package for specifying and solving convex problems [24], the computational and energy costs of doing so aboard a SatCom payload is typically prohibitive. In this work, we propose alternative algorithms that can be implemented on energy-efficient neuromorphic chipsets and leverage their event-driven operation.

Since neuromorphic chips can only tackle real-valued problems, we define the real-valued quantities

$$\widetilde{\boldsymbol{w}} = \begin{bmatrix} \Re \{ \boldsymbol{w}^{\mathrm{T}} \} \ \Im \{ \boldsymbol{w}^{\mathrm{T}} \} \end{bmatrix}^{\mathrm{T}} \in \mathbb{R}^{2N \times 1}, \quad (4)$$

$$\widetilde{\boldsymbol{A}} \left( \widehat{\boldsymbol{\theta}}(t) \right) = \begin{bmatrix} \Re \{ \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right) \} & \Im \{ \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right) \} \\ -\Im \{ \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right) \} & \Re \{ \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right) \} \end{bmatrix} \in \mathbb{R}^{2N \times 2}, \quad (5)$$

$$\widetilde{\boldsymbol{R}}(t) = \begin{bmatrix} \Re \left\{ \widehat{\boldsymbol{R}}(t) \right\} & -\Im \left\{ \widehat{\boldsymbol{R}}(t) \right\} \\ \Im \left\{ \widehat{\boldsymbol{R}}(t) \right\} & \Re \left\{ \widehat{\boldsymbol{R}}(t) \right\} \end{bmatrix} \in \mathbb{R}^{2N \times 2N}, \quad (6)$$

to rewrite problem (3) as

$$\begin{array}{l} \underset{\widetilde{\boldsymbol{w}} \in \mathbb{R}^{2N \times 1}}{\text{minimize}} \quad \widetilde{\boldsymbol{w}}^{\mathrm{T}} \widetilde{\boldsymbol{R}}(t) \widetilde{\boldsymbol{w}} + \lambda \| \widetilde{\boldsymbol{w}} \|_{1} \\ \text{subject to} \quad \widetilde{\boldsymbol{A}} \left( \widehat{\boldsymbol{\theta}}(t) \right)^{\mathrm{T}} \widetilde{\boldsymbol{w}} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

$$(7)$$

Solutions to problem (7) can be approximated on neuromorphic hardware using the S-LCA [25]. To do so, we first note that the constraint in (7) is equivalent to the equality

$$\left\| \widetilde{\boldsymbol{A}} \left( \widehat{\boldsymbol{\theta}}(t) \right)^{\mathrm{T}} \widetilde{\boldsymbol{w}} - \begin{bmatrix} 1 & 0 \end{bmatrix}^{\mathrm{T}} \right\|_{2} = 0, \tag{8}$$

wherein  $\|\cdot\|_2$  is the  $\ell_2$ -norm of a vector. Hence, we can define a surrogate unconstrained problem for (7) by integrating the constraint in (8) into the LASSO's cost function, as follows:

$$\min_{\widetilde{\boldsymbol{w}} \in \mathbb{R}^{2N \times 1}} \|\boldsymbol{A}\widetilde{\boldsymbol{w}} - \boldsymbol{c}\|_2^2 + \lambda \|\widetilde{\boldsymbol{w}}\|_1, \tag{9}$$

in which we have defined

$$\boldsymbol{A} = \begin{bmatrix} \widetilde{\boldsymbol{A}} \left( \widehat{\boldsymbol{\theta}}(t) \right)^{\mathrm{T}} \\ \mu \widetilde{\boldsymbol{S}}(t) \end{bmatrix} \in \mathbb{R}^{2(N+1) \times 2N} \text{ and } \boldsymbol{c} = \begin{bmatrix} 1 \\ \mathbf{0}_{(2N+1) \times 1} \end{bmatrix},$$
(10)

with  $\widetilde{\boldsymbol{S}}(t)$  being a matrix square root of  $\widetilde{\boldsymbol{R}}(t)$  satisfying the equality  $\widetilde{\boldsymbol{R}}(t) = \widetilde{\boldsymbol{S}}(t)^{\mathrm{T}}\widetilde{\boldsymbol{S}}(t)$ , and  $\mu > 0$ .

<sup>&</sup>lt;sup>2</sup>The optimal estimation of the above-mentioned parameters is beyond the scope of this conference contribution.

The solutions to problem (9) can be encoded into the firing rates of a leaky-integrate-and-fire spiking neural network (LIF-SNN) via the S-LCA (see [25] for details). To do so, we define a LIF-SNN as a directed graph of 2N spiking neurons operating over discrete time steps  $\ell \in \{1, \ldots, L\}$ . We denote as  $f_{\ell} \in \mathbb{R}^{2N \times 1}$  the instantaneous firing rates of neurons in the LIF-SNN. At each time step, the operation of the 2N neurons is defined by their currents  $i_{\ell} \in \mathbb{R}^{2N \times 1}$ , voltages  $v_{\ell} \in \mathbb{R}^{2N \times 1}$ , spiking outputs  $o_{\ell} \in \{0, 1\}^{2N \times 1}$ , and connectivity matrix  $C = -(A^{T}A - I_{2N})$ . For  $\ell \in \{1, \ldots, L\}$ , the outputs of the LIF-SNN are obtained recursively as

$$\boldsymbol{i}_{\ell} = (1 - \alpha)\boldsymbol{i}_{\ell-1} - (\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A} - \boldsymbol{I}_{2N})\boldsymbol{f}_{\ell}, \qquad (11)$$

$$\boldsymbol{v}_{\ell} = \boldsymbol{v}_{\ell-1} + \boldsymbol{A}^{\mathrm{T}}\boldsymbol{c} - \lambda \boldsymbol{1}_{2N\times 1} + \boldsymbol{i}_{\ell}, \qquad (12)$$

$$\boldsymbol{o}_{\ell} = \chi_{\{\boldsymbol{v}_{\ell} \succ \vartheta \mathbf{1}_{2N\times 1}\}},\tag{13}$$

with no leakage of the voltage compartment and with fixed excitatory current  $\mathbf{A}^{\mathrm{T}}\mathbf{c} - \lambda \mathbf{1}_{2N \times 1}$ , where  $\mathbf{1}_{2N \times 1}$  is a  $2N \times 1$  vector filled with 1s. Notation-wise, we have the decay value  $\alpha \in (0, 1)$ ; the firing threshold  $\vartheta > 0$ ; the inequality in (13) is defined elementwise; and  $\chi_{\{\cdot\}}$  is the indicator function. The algorithmic time horizon L is chosen such that the instantaneous firing  $\mathbf{f}_{\ell}$  of the neurons converges to the solution of problem (9) [25].

The latest version of Intel's Loihi chipset features graded spikes, that is, the output of spiking neurons is not restricted to  $\{0, 1\}$  but to an alphabet  $\{0, ..., K - 1\}$ , with K > 1. An alternative version of the S-LCA, namely the S-LCA-GS, can be used to solve problem (7) using graded spikes. Solutions are computed iteratively through the recursion

$$\widetilde{\boldsymbol{w}}_{\ell+1} = -\alpha_{\ell} \widetilde{\boldsymbol{R}}(t) \widetilde{\boldsymbol{w}}_{\ell} - \beta_{\ell} \widetilde{\boldsymbol{A}} \left( \widehat{\boldsymbol{\theta}}(t) \right) \boldsymbol{\delta}(\widetilde{\boldsymbol{w}}_{\ell}), \qquad (14)$$

where  $\alpha_{\ell} > 0$  is the learning rate,  $\beta_{\ell} > 0$  is the constraintcorrection rate, and for  $k \in \{1, 2\}$  and  $\delta_k = [\widetilde{\boldsymbol{A}} \left(\widehat{\boldsymbol{\theta}}(t)\right)^{\mathrm{T}} \widetilde{\boldsymbol{w}}_{\ell}]_k$ , we have

$$\left[\boldsymbol{\delta}(\widetilde{\boldsymbol{w}}_{\ell})\right]_{k} = \begin{cases} \mathcal{Q}\left(\delta_{k}-1\right), & \text{if } \delta_{k} > 1, \\ 0, & \text{if } \delta_{k} \leq 1, \end{cases}$$
(15)

with  $\mathcal{Q}(\cdot)$  denoting the quantization operation to the graded spike levels.

### V. SIMULATION RESULTS

In this section, we first describe the simulation scenario, the dataset used in our experiments, and the benchmark technique. We then validate the proposed LASSO approach through MATLAB-based numerical experiments by showcasing its effectiveness in selected samples of the dataset. Last, we evaluate the performance of the proposed NP-oriented approaches, which rely on the S-LCA and S-LCA-GS, for the entire dataset using Intel's Lava simulator.

#### A. Scenario Description, Dataset, and Benchmark

For assessing the performance of the beamforming techniques, we considered Equatorial medium-Earth orbit (MEO) satellites at an altitude of 8063 km, similar to the commercial SES's O3b mPower system. Focusing on the receive DBF design, we concentrated on the user uplink in the Ka-band, between 29.5 GHz and 30.0 GHz. The simulation setup was built with an aeronautical dataset consisting of time-varying airplane coordinates obtained from [20]. From the dataset, we selected a subset of 29 aircraft. To each aircraft we assigned an index AC  $\in \{1, \ldots, 29\}$ . For the simulations, we considered 37 snapshots, indexed by  $SS \in \{1, \ldots, 37\}$ , and for each snapshot SS, we calculated the corresponding 2D relative aircraft's location  $\boldsymbol{\theta}(t_{\rm SS}) = [\phi(t_{\rm SS}) \ \theta(t_{\rm SS})]^{\rm T}$  from the satellite's viewpoint, with  $t_{SS+1} - t_{SS} \approx 1$  min on average. Overall, the dataset was composed of  $29 \times 37 = 1073$  aircraftsnapshot pairs, which were indexed by (AC, SS). Fig. 1 (see p. 2) illustrates the trajectory of one of these aircraft and its serving satellite. A clear-sky channel model was considered, for the aircraft were above the clouds.

Regarding the UPA at the satellite platform, we considered the following characteristics:  $25\lambda \times 25\lambda$  in size;  $50 \times 50$  radiating elements;  $5 \times 5$  subarrays;  $10 \times 10$  RFCs; and  $0.5\lambda$  interelement spacing. Furthermore, we assumed an interferencefree scenario with just one aircraft uploading signals. In this case, the estimation of the covariance matrix in (2) was done considering perfect knowledge of the parameters  $\sigma_s^2$  and  $\sigma_n^2$ , whereas the channel power  $P_h$  was estimated numerically from the entries of the vector in (1),  $y_n(t)$ , as

$$\widehat{P_h}(t) = \frac{1}{\sigma_s^2} \left( \frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} |y_n(t)|^2 - \sigma_n^2 \right), \quad (16)$$

where  $\mathcal{N}$  is the set of antenna elements used for the computation. Note that some are unavailable due to the turning off of the RFCs in the proposed approaches. In addition, in order to emulate an imperfect knowledge of the angles-of-arrival (i.e., azimuth and elevation angles),  $\hat{\theta}(t_{\rm SS})$  was modeled as the average between the two latest actual snapshot values, i.e.,  $\theta(t_{\rm SS})$  and  $\theta(t_{\rm SS-1})$ . Furthermore, we set SNR = 4 dB and  $\lambda = 10^{-7}$  and, for the proposed sparsity-promoting approaches, we zeroed the coefficients on  $\Re \{w\}$  that contributed to less than 1% of the energy of this vector; we did the same for the imaginary part as well.

As a benchmark, we adopted the conventional MVDR beamforming [17], which does not account for sparsity. It addresses the problem

$$\begin{array}{ll} \underset{\boldsymbol{w} \in \mathbb{C}^{N \times 1}}{\text{minimize}} & \boldsymbol{w}^{\mathrm{H}} \widehat{\boldsymbol{R}}(t) \boldsymbol{w} \\ \text{subject to} & \boldsymbol{a} \left( \widehat{\boldsymbol{\theta}}(t) \right)^{\mathrm{H}} \boldsymbol{w} = 1 \,, \end{array}$$

$$(17)$$

obtaining the closed-form solution

$$\boldsymbol{w}_{\text{MVDR}} = \frac{\left(\widehat{\boldsymbol{R}}(t)\right)^{-1} \boldsymbol{a}\left(\widehat{\boldsymbol{\theta}}(t)\right)}{\boldsymbol{a}\left(\widehat{\boldsymbol{\theta}}(t)\right)^{\text{H}} \left(\widehat{\boldsymbol{R}}(t)\right)^{-1} \boldsymbol{a}\left(\widehat{\boldsymbol{\theta}}(t)\right)} .$$
(18)

# B. LASSO Validation

Table I shows the sparsity level results achieved with the proposed LASSO approach when generating beams for a set



Fig. 2: Beam patterns for both azimuth,  $\phi$ , and elevation,  $\theta$ , angles. The selected dataset point was (AC,SS) = (4, 12). The vertical dashed lines show the azimuth/elevation angles corresponding to the actual relative aircraft position.

LASSO DBF solved with MATLAB's CVX			
(AC,SS)	Real	Imaginary	Complex
(4,2)	22%	19%	41%
(4,12)	22%	18%	40%
(20,2)	21%	21%	42%
(20,12)	21%	18%	39%

TABLE I: Percentage of nonzero entries of the DBF vector

of 4 selected (AC, SS) pairs. In the table, the smaller the percentage value (relative number of nonzero entries), the higher the sparsity level. The percentage of nonzero entries of the complex-valued coefficients was around 40%, implying that about 60% of the RFCs could be turned off without compromising the resulting beam pattern. Regarding the MVDR benchmark, all its coefficients were nonzero, as expected, thus not allowing any RFC to be turned off.

Fig. 2 depicts an example of the obtained beam patterns corresponding to the pair (AC, SS) = (4, 12) and employing the MVDR benchmark and the proposed LASSO algorithms. The vertical dashed lines in the plots show the azimuth/elevation angles corresponding to the actual relative aircraft position. Since we considered outdated information regarding the aircraft's location, the main beams appear slightly shifted from the aircraft's actual position (in this particular example, this is clearer for the azimuth beam pattern plotted in blue). This highlights the need for fast adaptation of the beamforming coefficients to enable the tracking of fast-moving users. This figure shows that the LASSO beamforming strategy performed as well as the MVDR benchmark when it comes to the main lobes reasonably matching the aircraft's location. Thus, the promoted sparsity of the proposed technique (reported in Table I) did not hamper the ability to generate the main radiation lobe toward the target device. On the other hand, the LASSO beam pattern experiences high values (higher than 0 dB) over a much wider range of azimuth/elevation angles, which is a disadvantage. Nonetheless, the results in the next section indicate that the LASSO beamformer's average output power is on par with the MVDR's.

#### C. Performance Assessment of the NP-oriented Approaches

In order to go beyond a visual comparison among beam patterns and holistically evaluate the proposed NP-oriented beamforming for all the 1073 samples in the dataset, we considered a single figure of merit summarizing the beamforming behavior, namely the normalized beamformer's average output power,  $\rho$ . This quantity corresponds to the normalized version of the MVDR benchmark cost function in (17), being mathematically defined as

$$\rho = \frac{\boldsymbol{w}^{\mathrm{H}} \boldsymbol{R} \boldsymbol{w}}{\max_{\mathrm{AC,SS}} \{ \boldsymbol{w}_{\mathrm{MVDR}}^{\mathrm{H}} \widehat{\boldsymbol{R}} \boldsymbol{w}_{\mathrm{MVDR}} \}} \,. \tag{19}$$

The lower the cost-function value, the better the beamforming capabilities to focus on the desired signal direction while mitigating the effects of noise and interference. This interpretation assumes that the beamformer is pointing toward the desired direction since the weights satisfy a corresponding linear constraint; all the algorithms considered in this work belong to this category (prior to the zeroing process of the negligible coefficients).

Fig. 3 depicts a comparison among the normalized beamformer's average output powers,  $\rho$ , obtained with all the algorithms described in the paper. This figure considers all the 1073 samples in the dataset. It can be seen in Fig. 3 that the neuromorphic algorithms generally provided comparable results to the benchmarks, indicating they can attain similar performance in terms of pointing toward the desired direction while avoiding capturing unwanted signals. The only technique with a somewhat different behavior was the S-LCA, with a smaller median value for  $\rho$  but a much wider spread, which



Fig. 3: Statistics of the normalized beamformer's average output power,  $\rho$ , defined in (19). Each box shows the median as the central mark (in red), with the 25th and 75th percentiles indicated by the bottom and top edges of the blue box, respectively. The whiskers extend to the most extreme data points that are not considered outliers.

confers some uncertainty regarding the actual performance in a particular situation.

As a final point, it is noteworthy that both the S-LCA and S-LCA-GS achieved remarkable sparsity levels, comparable to the LASSO DBF design. On average, we observed that around 60% of the RFCs could be turned off when using them.

### VI. CONCLUSIONS

This work tackled the problem of designing digital beamforming using onboard neuromorphic processors deployed on NGSO satellite systems serving fast-moving users like aircraft. Starting from the MVDR beamforming, we proposed a novel problem formulation, including a sparsity-promoting penalty term, aiming at minimizing the number of active onboard RFCs. The resulting problem, called proposed LASSO, served as the fundamental building block from which we further proposed an implementation with suitable NP-oriented algorithms, namely S-LCA and S-LCA-GS, which were validated in Intel's open-source software Lava, the main programming tool for Intel's neuromorphic chips. The results underscored the comparable performance of neuromorphic algorithms compared to the benchmarks (MVDR and proposed LASSO). Indeed, S-LCA and S-LCA-GS achieved high sparsity levels, enabling turning off around 60% of the RFCs, thus demonstrating the efficacy of these algorithms in promoting sparsity while maintaining the beamforming performance. Future works include implementing the proposed NP-oriented solutions on Intel's Loihi 2 chipset and assessing energy consumption and time taken to converge to a solution (delay).

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