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Review: Wideband Spectrum Sensing for Next Generation Wireless Networks

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Abstract

Next generation wireless networks are expected to operate in licensed, shared as well as unlicensed spectrum. To enable this, central controller or base stations need wideband spectrum sensing (WSS) to periodically identify potential spectrum resources and allocate them to the desired users. The main challenge in WSS is the requirement of prohibitively high sampling rate analog-to-digital converters (ADC) which are area and power hungry. To overcome this bottleneck, sub-Nyquist sampling based WSS (SNS-WSS) techniques have been discussed in the literature. The SNS-WSS exploits the sparse nature of a wideband spectrum and hence, accomplish WSS using low-rate ADCs. In this paper, we review and compare the advantages and drawbacks of existing SNS-WSS. We also discuss future research directions for making SNS-WSS feasible in next generation wireless networks.

1 Introduction

In order to meet high data rate requirements of futuristic delay-sensitive multimedia services and support ultra-dense networks with very high peak rate but relatively lower expected traffic per user, next-generation networks are envisioned on a revolutionary path of spectrum sharing mechanism [1]. They are expected to operate not only in the licensed spectrum but also in the shared (2.3 GHz/ 3.5 GHz) as well as an unlicensed spectrum (2.4 GHz / 5-7 GHz / 57-71 GHz) [2]. Thus, central controller or base stations need to periodically perform wideband spectrum sensing (WSS) to identify and allocate the spectrum resources to users to meet their services and application requirements. Since base stations are required to communicate to determine transmission parameters for each user, they need to estimate other parameters such as signal-to-noise ratio, modulation scheme, interference level, protocol in addition to occupancy status (vacant/busy).

Various spectrum sensing and parameter estimation methods [3] such as energy detector, cyclostationary detector, wavelet-based detector, cumulant-based classifiers have been explored in the literature. However, these methods are applicable only to the Nyquist sampled narrowband signals. Since the WSS needs to be performed on the spectrum that ranges from 300 MHz to 30 GHz, the use of traditional methods will require prohibitively high rate analog-to-digital converters (ADC) which is computationally expensive and power inefficient.

In the last decade, various sub-Nyquist sampling (SNS) based WSS (SNS-WSS) methods have been proposed to overcome the need for high-speed ADCs. These methods exploit the sparsity of the wideband spectrum to generate sub-Nyquist samples via low rate ADCs. These sub-Nyquist samples are then utilized in various ways to determine various parameters of the wideband spectrum. In this paper, we review popular SNS-WSS methods as shown in Fig. 1 along with their advantages and drawbacks. We also discuss future research directions to make SNS-WSS methods feasible in practice.

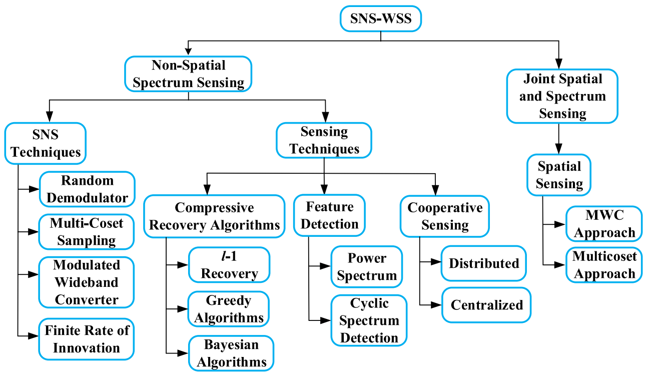

Figure 1. Classification of the various wideband spectrum sensing methods

2 Sub-Nyquist Sampling Techniques

In this section, we discuss four state of art SNS techniques mentioned in Fig. 1.

2.1 Random Demodulator (RD)

The RD [4], as shown in Fig. 2, has a pseudo-random sequence generator, a mixer, an accumulator and an ADC. The RD demodulates a multi-tone wideband signal, $x(t)$ by mixing it with a pseudo-random sequence of ± 1 that is generated at a Nyquist rate of $x(t)$. The demodulated signal is now passed through an accumulator and ADC to generate sub-Nyquist samples at a rate of $R\ Hz$. This step corresponds to an integrate and dump operation where the demodulated signal is integrated for the duration $\frac{1}{R}$ and then

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reset to its initial value. Here, integration duration, R is decided such that it is always greater than $2K$ where K is the maximum possible number of active tones in $x(t)$. The major limitation of RD is that it is valid only for a multi-tone signal Since the wideband signals are analog in nature and hence contains infinite number of tones. RD based digitization becomes computationally expensive.

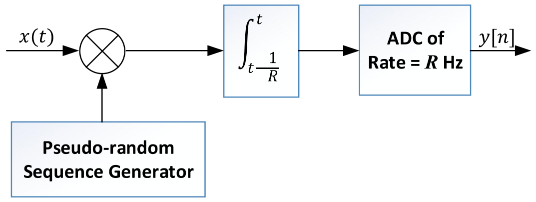

Figure 2. Block diagram of random demodulator

2.2 Multi-Coset Sampling (MCS)

Unlike RD which generates samples via single low rate ADC, the MCS [5] uses p synchronized ADCs for the digitization. MCS uniformly samples a wideband analog signal, $x(t)$ consisting of maximum K transmissions via $p > 2K$ parallel ADCs at a rate of $\frac{1}{LT}$ where $p << L$, L (as shown in Fig. 3(b)) is the number of frequency sub-bands into which a wideband spectrum is divided and T is the Nyquist period of $x(t)$. All p ADCs samples at a distinct time offset, $c_i \in \{1,2,..L\}$ $\forall$ $i = [1,p]$ w.r.t. initial sample. As shown in Fig. 3(a), for a given c_i, the output of each ADC is an active coset. By using the Poisson summation formula, the discrete time Fourier transform (DTFT) of all active cosets can be represented as

$$\mathbf{Y}(f) = \mathbf{A}_{mcs}\mathbf{X}(f) \qquad \forall f \in [0, 1/LT] \tag{1}$$

where $\mathbf{Y}(f)$ represents $p \times 1$ vector containing DTFT of samples obtained at every ADC as its rows, $\mathbf{A}_{mcs}$ is a $p \times L$ partial Fourier matrix and $\mathbf{X}(f)$ is a $L \times 1$ vector consisting of Fourier transform of L frequency sub-bands as its rows.

MCS follows a straight forward approach to generate low rate samples, but it suffers from various limitations. First, due to the requirement of time delays of order pico-second, it is difficult to achieve synchronization between ADCs. Second, due to the processing of direct RF signal, it requires high analog bandwidth. To overcome these drawbacks, MWC and FRI SNS techniques have been explored.

2.3 Modulated Wideband Converter (MWC)

The MWC [6] has $p > 2K$ analog branches where its each branch follows the architecture of RD, i.e., each branch of MWC has a pseudo-random sequence generator, a mixer, an accumulator and an ADC. However, unlike RD, the pseudo-random sequences (or mixing functions), $m_i(t)$ $\forall$ $i \in [1,p]$, of every branch are uncorrelated periodic sequences of time period $= LT$. Because of the periodic nature, $m_i(t)$ contains harmonics at rate of $f_p = 1/LT$. Hence, as shown in Fig. 3(c), the DTFT of mixed demodulated samples generated at the output of MWC is a linear combination of lf_p shifted versions of all L frequency sub-bands. Mathematically, it can be represented as

$$\mathbf{Y}(f) = \mathbf{A}_{mwc}\mathbf{X}(f), \quad f \in [-f_p/2, +f_p/2] \tag{2}$$

where $\mathbf{Y}(f)$ is a $p \times 1$ vector consisting of the DTFT of samples obtained at p analog branches, $\mathbf{A}_{mwc}$ is a $p \times L$ sampling matrix and $\mathbf{X}(f)$ is vector of Fourier transform of L frequency sub-bands.

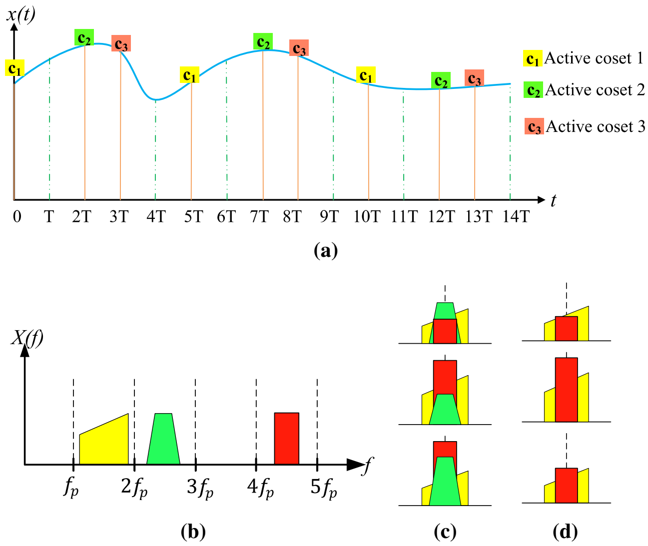

Figure 3. (a) Samples obtained at MCS for $c_i = \{0, 2, 3\}$, $p = 3$ and $L = 5$ (b) Wideband spectrum divided into $L = 5$ frequency sub-bands (c) DTFT of output at every branch of MWC (d) DTFT of output at every branch of FRI for $\beta = \{1, 2, 4, 5\}$

2.4 Finite Rate of Innovation (FRI)

The FRI architecture of SNS [8,9] is similar to the architecture of MWC. But instead of digitizing all L frequency sub-bands, FRI digitizes a set of desired frequency sub-bands, β. To perform this, the FRI uses a unique mixing functions, $m_i(t) = \sum_{n \in \beta} \alpha_{i,n}\, e^{-j2\pi f_n t}$ at its every analog branch. Due to this, the DTFT of the samples generated at the output of every analog branch, as shown in Fig. 3(d), is a linear combination of shifted copies of all frequency sub-bands present in β. Mathematically, it can be represented as

$$\mathbf{Y}(f) = \mathbf{A}_{fri}\mathbf{X}(f) \tag{3}$$

where $\mathbf{Y}(f)$ is a $p \times 1$ vector consisting of the DTFT of samples obtained at p analog branches, $\mathbf{X}(f)$ represents $|\beta| \times 1$ vector which contains Fourier transform of β frequency sub-bands and $\mathbf{A}_{fri}$ is a $p \times |\beta|$ matrix containing $\alpha_{i,n}$ as its $(i,n)^{th}$ entry.

3 Spectrum Sensing Techniques

The sub-Nyquist samples generated by any of the SNS techniques have been utilized by various spectrum sensing techniques to perform SNS-WSS by estimating transmission parameters like carrier frequency, bandwidth and modulation scheme. These sensing techniques can be broadly categorized as 1) sparse recovery of spectrum, 2) feature detection, 3) collaborative sensing and 4) spatial sensing.

Table 1. Comparison of state of art SNS techniques

	Pros	Cons
RD	• Requires single ADC	• Not applicable to analog signals • Contiguous WSS
MCS	• Can work on analog signals	• Needs accurate time delay of order 10^{-10}second • Requires high analog bandwidth of *GHz* • Contiguous WSS
MWC	• Needs smaller analog bandwidth	• Needs mixing function of rate in *GHz* • Contiguous WSS
FRI	• Non-contiguous WSS	• Reconstruction might not be possible if a transmission occupies two consecutive sub-bands

3.1 Sparse Recovery Algorithms

Recovery of the spectrum is the simplest way to determine the location of transmitting bands. Since the wideband signal $\mathbf{X}(f)$ is sparse in Eq. 1, 2 and 3, any sparse recovery algorithm can be used for its reconstruction. Various compressive sensing algorithms including l-1 minimization algorithms like BP and LASSO [10], greedy algorithms like orthogonal matching pursuit (OMP) [11] and a Bayesian approach based algorithms [12] have been studied to recover a sparse signal. The l-1 minimization based algorithms offer better reconstruction accuracy than greedy and Bayesian algorithms. But l-1 minimization is not feasible for real-time applications due to high computation time and complexity. OMP algorithm has low computational complexity, but it requires the prior knowledge of a number of occupied frequency sub-bands in $\mathbf{X}(f)$. Bayesian algorithms offer better reconstruction accuracy than greedy algorithms like OMP and have lower computational complexity than l-1 minimization based algorithms [13]. But Bayesian algorithms require the prior knowledge of the probability distribution of the information signal transmitted on the wideband spectrum.

3.2 Feature Detection

Feature detection based WSS has two major advantages over sparse recovery algorithms based WSS. First, the transmitted signals in a wideband spectrum consist of certain features like modulation scheme, stationary and cyclostationary property. These features have a fewer degree of freedom than the reconstruction of a sparse signal. Hence, feature-based WSS is applicable even if the sparsity of signal is low. Second, features like cyclostationary features are more robust to noise and hence, can be recovered at low SNR. SNS based power spectrum [14,15] and cyclostationary feature recovery [16,17] have been studied for WSS.

Power spectrum based WSS [14,15] assumes that the transmissions in a wideband signal are uncorrelated wide-sense stationary. With this assumption, the power spectrum of frequency bands can be determined from the sub-Nyquist samples, $\mathbf{Y}(f)$ by taking its autocorrelation i.e. $E[\mathbf{Y}(f)\mathbf{Y}^H(f)]$. Since the support vector (which contains the status of frequency sub-bands) of a wideband spectrum and its power spectrum is same, the recovery of the power spectrum is sufficient for WSS. On the other hand, cyclostationary based WSS [16,17] takes advantage of the statistical periodicity of a modulated signal and hence, can have cyclic spectrum. By recovering the cyclic spectrum from the shifted autocorrelation of samples, i.e. $E[\mathbf{Y}(f)\mathbf{Y}^H(f+a)]$, the carrier frequencies and their parameters like bandwidth, modulation scheme and symbol rate can be determined. Furthermore, since stationary noise does not exhibit spectrum correlation for $a \neq 0$, the desired signal can be easily separated from the noise making cyclostationary WSS more robust to noise.

3.3 Collaborative Spectrum Sensing (CSS)

The wideband signal received at a user or base station suffers from channel fading, shadowing and path losses. To reduce the impact of these channel imperfections on spectrum sensing, the CSS approach allows the sharing of sensing information among the users to provide spatial diversity gain. Based on the sharing method, the CSS can be categorized as 1) Centralized CSS and 2) Distributed CSS. In the centralized CSS, all users share the signal's information collected by them with a fusion centre which jointly determines the final support vector. Whereas in distributed CSS, all users share the signal's information collected by them with their neighbouring users and then iterative converge to the final estimate. As centralized CSS makes decision based on the information received from all users, it has higher diversity gain than the distributed CSS. But it has higher power consumption and the possibility of link failure as compared to distributed CSS. In [18], centralized CSS has been performed where the autocorrelation of sub-Nyquist samples generated at every user is shared with the fusion centre to jointly estimate the carrier frequencies. Whereas in [19], distributed CSS has been exploited where all users make their local decision on the spectrum occupancy status from their respective sub-Nyquist samples and then share their binary decision with neighbouring users to make the final decision.

4 Joint Spectrum and Spatial Sensing

Using spatial sensing approach, base stations/users estimate the direction-of-arrival of the occupied spectrum bands. This not only helps the base station to take well-informed decisions for resource allocation but also opens up transmission opportunities in the spatial direction.

Multi-coset spatial sensing: Spatial sensing performed in [21–23] employ MCS in antenna array architecture. In [21], MCS architecture is used at every antenna of a uniform linear array (ULA) of antennas. Hence, if there are K number of antennas, then this architecture requires $K.p$ number of ADCs for sensing K transmissions. To reduce the hardware complexity, [22] considers L-shaped antenna array where each antenna has a direct branch and a delayed branch of delay τT (where $0 < \tau < 1$). Here, the received wideband signal and its delayed version are sampled at a low rate of $\frac{1}{LT}$ and to determine the carrier frequencies and DOAs, ESPIRIT and MUSIC algorithms are used. As compared to [21], this architecture requires only $2K$ number of ADCs. To further reduce the hardware complexity, [23] uses a uniform rectangular array of M antennas and a delayed channel network containing p delayed channels at one antenna. [23] shows that with this setup, it can determine up to $M(p-1)/4$ carrier frequencies and DOAs.

MWC spatial sensing: The multi-coset spatial sensing architectures suffer from the drawbacks of the MCS method of SNS. To overcome these drawbacks, compressed carrier & DOA estimation (CASCADE) method [24] is proposed. This method employs the MWC model which consists of a mixing function followed by LPF and low rate sampler at every antenna of the L-shaped antenna array. The joint ESPIRIT algorithm is applied to the sub-Nyquist samples to perform joint estimation of carrier frequencies and their respective DOAs. However, for K number of transmissions CASCADE requires minimum $2K$ antennas/ADCs which is higher than [23].

5 Future Research Directions

In this section, we identify the future research directions for making SNS-WSS feasible in next generation wireless networks.

1. *Sparse basis:* The existing SNS-WSS methods are applicable only if a wideband signal is sparse in the frequency domain. But with the deployment of the cognitive radio network, a wideband spectrum will no longer remain sparse in the frequency domain. So, there is a need to explore a new basis in which wideband spectrum will be sparse.

2. *Adaptive SNS architecture for WSS:* The existing SNS-WSS methods make the assumption on the prior knowledge of spectrum sparsity [4–6, 11, 12]. Since the sparsity of the wideband spectrum varies with time, there is a need for an adaptive SNS-WSS architecture which can dynamically adapt to sparsity level of the signal.

3. *Deep Learning for WSS:* Deep learning approaches have shown to considerably outperform conventional machine learning approaches. It would be interesting to explore deep learning which can automatically reconstruct wideband spectrum from SNS samples.

4. *Non-contiguous spatial sensing:* The existing spatial sensing methods [21–24] consider the sensing of entire wideband spectrum. So, if the number of transmitting users exceeds the upper limit of the spatial sensing model, then the spatial sensing techniques may not guarantee accurate estimation.Hence, non-contiguous sensing which offers control over number and locations of frequency sub-bands need to be explored. Such an approach also needs online learning algorithms to choose the frequency sub-bands in order to guarantee accurate estimation.

5. *Hardware prototype:* There has not been significant work which deals with experimental validation of SNS-WSS techniques in the real radio environment. Existing prototypes [7] do not consider DOA estimation and non-contiguous sensing. Furthermore, a reconfigurable architecture capable of adapting its parameters on-the-fly needs to be explored.

References

[1] S. Parkvall, E. Dahlman, A. Furuskar and M. Frenne, “NR: The New 5G Radio Access Technology,” *IEEE Communications Standards Magazine*, **1**, 4, Dec. 2017, pp. 24-30, doi: 10.1109/MCOMSTD.2017.1700042

[2] J. Jeon, “NR Wide Bandwidth Operations,” *IEEE Communications Magazine*, **56**, 3, March 2018, pp. 42-46, doi: 10.1109/MCOM.2018.1700736

[3] Y. Zeng, Y. C. Liang, A. T. Hoang and R. Zhang, “A review on spectrum sensing for cognitive radio: challenges and solutions,” *EURASIP Journal on Advances in Signal Processing*, **2010**, 2, Jan. 2010, pp. 1-15, https://doi.org/10.1155/2010/381465.

[4] J. A. Tropp, J. N. Laska, M. F. Duarte, J. K. Romberg and R. G. Baraniuk, “Beyond Nyquist: Efficient Sampling of Sparse Bandlimited Signals,” *IEEE Trans. on Inf. The.*, **56**, 1, Jan. 2010, pp. 520-544, doi: 10.1109/TIT.2009.2034811

[5] M. Mishali and Y. C. Eldar, “Blind multi-band signal reconstruction: Compressed sensing for analog signals,” *IEEE Trans. Signal Process.*, **57**, 3, Mar. 2009, pp. 993-1009, doi: 10.1109/TSP.2009.2012791

[6] M. Mishali and Y. C. Eldar, “From Theory to Practice: Sub-Nyquist Sampling of Sparse Wideband Analog Signals,” *IEEE J. Sel. Topics Signal Process.*, **4**, 2, April 2010, pp. 375-391, doi: 10.1109/JSTSP.2010.2042414

[7] M. Mishali, Y. C. Eldar, O. Dounaevsky, and E. Shoshan, “Xampling: Analog to Digital at Sub-Nyquist Rates,” *IET Circuits, Devices and System*, **5**, 1, Jan. 2011, pp. 8-20, doi: 10.1049/iet-cds.2010.0147

[8] K. Gedalyahu, T Ronen and Y. C. Eldar, “Multichannel Sampling of Pulse Streams at the Rate of Innovation,” *IEEE Trans. Signal Process.*, **59**, 4, April 2011, pp. 1491-1504, doi: 10.1109/TSP.2011.2105481

[9] S. Bagheri and A. Scaglione, “The Restless Multi-Armed Bandit Formulation of the Cognitive Compressive Sensing Problem,” *IEEE Trans. Signal Process.*, **63**, 5, March 2015, pp. 1183-1198, doi: 10.1109/TSP.2015.2389620

[10] E. J. Candes, M. B. Wakin, and S. P. Boyd,“Enhancing sparsity by reweighted *l*-1 minimization,” *Journal of Fourier analysis and applications*, **14**, 5, Dec. 2008, pp. 877-905, https://doi.org/10.1007/s00041-008-9045-x

[11] J. D. Blanchard, M. Cermak, D. Hanle and Y. Jing, “Greedy Algorithms for Joint Sparse Recovery,” *IEEE Trans. Signal Process.*, **62**, 7, April 2014, pp. 1694-1704, doi: 10.1109/TSP.2014.2301980

[12] L. Yu, H. Sun, J. P. Barbot and G. Zheng, “Bayesian compressive sensing for cluster structured sparse signals”, *Elsevier: Signal Processing*, **92**, 1, Jan. 2012, pp. 259-269, https://doi.org/10.1016/j.sigpro.2011.07.015

[13] Y. Arjoune, N. Kaabouch, H. E. Ghazi and A. Tamtaoui, “Compressive sensing: Performance comparison of sparse recovery algorithms,” *IEEE Computing and Communication Workshop and Conference*, Jan. 2017, pp. 1-7, doi: 10.1109/CCWC.2017.7868430

[14] D. D. Ariananda and G. Leus, “Compressive wideband power spectrum estimation,” *IEEE Trans. Signal Process.*, **60**, 9, Sept. 2012, pp. 4775-4789, doi: 10.1109/TSP.2012.2201153

[15] D. Cohen and Y. C. Eldar, “Sub-Nyquist sampling for power spectrum sensing in cognitive radios: A unified approach,” *IEEE Trans. Signal Process.*, **62**, Aug. 2014, pp. 3897-3910, doi: 10.1109/TSP.2014.2331613

[16] Z. Tian, Y. Tafesse and B. M. Sadler, “Cyclic Feature Detection With Sub-Nyquist Sampling for Wideband Spectrum Sensing,” *IEEE J. of Sel. Topics Signal Process.*, **6**, 1, Feb. 2012, pp. 58-69, doi: 10.1109/JSTSP.2011.2181940

[17] D. Cohen and Y. C. Eldar, “Sub-Nyquist Cyclostationary Detection for Cognitive Radio,” *IEEE Trans. Signal Process.*, **65**, 11, June 2017, pp. 3004-3019, doi: 10.1109/TSP.2017.2684743

[18] D. D. Ariananda and G. Leus, “Cooperative compressive wideband power spectrum sensing,” *Proc. IEEE Asilomar Conf. Signals, Systems and Computers*, Nov. 2012, pp. 303âĂŞ307, doi: 10.1109/ACSSC.2012.6489012

[19] Z. Tian, “Compressed wideband sensing in cooperative cognitive radio networks,” *IEEE Global Communications Conf.*, pp. 1-5, U.S., Dec. 2008,doi: 10.1109/GLOCOM.2008.ECP.721

[20] F. Zeng, C. Li, and Z. Tian, “Distributed compressive spectrum sensing in cooperative multihop cognitive networks,” *IEEE J. Sel. Topics Signal Process.*, **5**, 1, Feb. 2011,pp. 37-48, doi: 10.1109/JSTSP.2010.2055037

[21] D. D. Ariananda and G. Leus, “Compressive joint angular-frequency power spectrum estimation,” *IEEE European Signal Processing Conference*, Sep. 2013, pp. 1-5.

[22] A. A. Kumar, S. G. Razul and C. M. S. See, “An efficient sub-Nyquist receiver architecture for spectrum blind reconstruction and direction of arrival estimation,” *IEEE International Conference on Acoustics, Speech and Signal Processing*, April 2014, pp. 6781-6785.

[23] A. A. Kumar, M. G. Chandra and P. Balamuralidhar, “Joint frequency and 2-D DOA recovery with sub-Nyquist difference space-time array,” *IEEE 25th European Signal Processing Conference*, Sept. 2017, pp. 400-404.

[24] S. Stein Ioushua, O. Yair, D. Cohen and Y. C. Eldar, “CaSCADE: Compressed Carrier and DOA Estimation,” *IEEE Trans. Signal Process.*, **65**, 10, May 2017, pp. 2645-2658, doi: 10.1109/TSP.2017.2664054