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BRIEF COMMUNICATION

Sub-Nyquist spectrum sensing and learning challenge

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1 Introduction

The fact that the spectrum resource is underutilised in certain bands has motivated the dynamic spectrum access (DSA) approach, which enables unlicensed secondary users (SUs) equipped with cognitive radio (CR) devices to access the spectrum without causing significant interference to primary users (PUs). Nowadays, the increasing bandwidth for wireless communication in millimetre-wave and Terahertz frequency bands puts higher requirements on the performance of spectrum sensing technique, the primary enabler of DSA. Traditional Nyquist-rate sampling and processing tend to be impractical due to high power consumption, high-cost, and hardware complexity of high-speed analogue to digital converters (ADCs). To overcome the sampling rate bottleneck, several sub-Nyquist sampling methods [1–9], recovery algorithms [10–18] and channel detection methods [19–23] have been proposed. Moreover, the recent advancements in machine-learning-based spectrum sensing have been characterised, which has provided further intelligence to CR devices with better adaptivity and higher flexibility under complex radio environments [24–30].

Still, the performance demands placed on sub-Nyquist spectrum sensing creates many different challenges, which comprise, but are not limited to, the following:

- For compressive samplers, the necessary sampling rate to successfully reconstruct a sparse signal is determined by the actual sparsity order (the ratio of the occupied channel to the total sensing bandwidth) of the signal. On the other hand, spectrum reconstruction based on a greedy algorithm requires prior knowledge of spectrum sparsity as an input. However, due to the uncertainty in the environment, the spectrum sparsity is always unknown and unpredictable. In practice, the sampling rate has to be chosen conservatively, according to the upper bound of the actual sparsity order instead of the real sparsity, which can be unnecessarily high, causing waste of sampling resources and computational burden, while the existing cross-validation algorithms are still compute-intensive [12, 31].
- The spectrum dynamically changes over time. In practice, long-time statistical method should be avoided during the sensing stage to improve robustness, while the compressive recovery performance tends to deteriorate as the sampling window being shortened [32]. How to choose the suitable sampling windows is another challenge.
- Algorithms to recover the spectrum from sub-Nyquist samples are often computationally intensive. It is desirable to spend as little time as possible on spectrum sensing to improve transmission efficiency and to reduce interference to PUs.
- The transmission of the existing SUs should also be detected by the subsequent accessors. The coexistence of a large number of SUs can influence the spectrum sparsity, even beyond the capacity of the sub-Nyquist spectrum sensing device.

For stimulating novel approaches and designs on sub-Nyquist spectrum sensing and learning task. A challenge is issued with a reference sub-Nyquist algorithm, open data sets and awards up to 10,000 USD. It is hoped to promote relative research and facilitate the theory-to-practice process of promising ideas.

2 The challenge

Several Nyquist-rate time-domain data sets on baseband with GHz bandwidth are provided. In the meantime, basic MATLAB

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and LabVIEW codes of a sub-Nyquist sampling scheme with fundamental recovery algorithms are released for reference on the challenge website. The participants will be required to sense the spectrum from the given data sets as accurately as possible with a relatively lower average sampling rate at smaller computational cost. The participants will be judged on

- The sensing ability and reconstruction accuracy of proposing approaches with the given data sets;
- The robustness, complexity and real-time performance of proposing approaches working on real-world signal with our software-defined radio (SDR) test platform as shown in Section 6.

Team entrants are encouraged. Extra credits will be allocated to innovative methods.

3 Submission requirements

An overall sub-Nyquist spectrum sensing solution is requested, including the following two parts in general, with innovation or improvement in both or individual part.

- Sub-Nyquist Sampling architecture (include but not limited to analog-to-digital converter, modulated wideband converter and multicoset sampler, etc.);
- Recovery & detection algorithms.

The documents for submission include

- MATLAB or Python code for processing the given data sets;
- LabVIEW code for processing real-time data on the NI SDR test platform;
- Algorithm and software design manual;
- A concept paper demonstrating the sampling architecture and recovery & detection algorithms.

4 Challenge criteria

The submitted entries will be evaluated by the authors team and a few other experts in the field according to the criteria shown in Table 1.

5 The data sets

We provide data sets composed of digital samples of real wideband signal for participants to test their algorithms, the properties of the data sets are shown in Table 2. The data sets are composed of 500~60000pts raw continuous baseband I/Q samples sampled with 3.072GHz rate. 1~3 100MHz active channels may exists among the –1GHz~1GHz baseband. For the receiver, the positions of the active carriers are previously unknown. The data sets are available to be downloaded on the challenge website.

Table 1 Criteria for evaluating the entries

	Criteria	Weight
Collection, Performance & Analysis	Approach ingenuity	15%
	Sensing / detecting performance	25%
	Sampling cost	10%
	Computational cost	10%
Code & Documentation	Source code[1)] (MATLAB/Python and LabVIEW)	25%
	Hardware & software design manual	15%

Table 2 Properties of the data sets provided for test

Signal	Symbols	Pseudorandom symbols
	Modulation type	64-QAM
	Multiplexing	Verizon 5G OFDM
	Channel bandwidth	100MHz
	Active channel number	1~3 channels without knowledge on positions
	Spanning	Up to 2GHz
Receiver	Baseband bandwidth	2GHz (complex)
	Sampling frequency	3.072GHz
Data	Data type	Raw continuous samples from baseband IQ channels
	Window lengths	500~60000pts

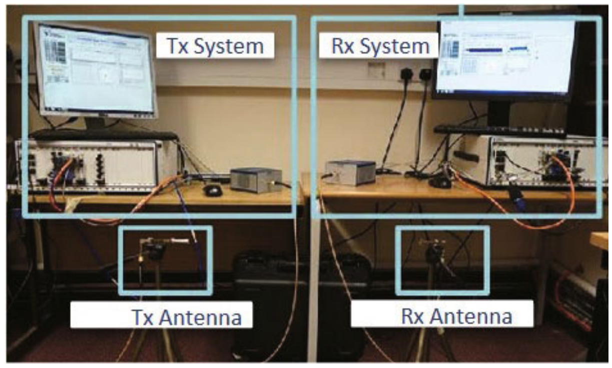

Fig. 1 NI Millimetre-wave transceiver system

6 Test platform

The submitted approaches will be tested on a hardware platform comprised of the NI mmWave SDR systems, used as the transmitter and receiver, respectively (Fig. 1). The transmitter and receiver have modular configurable hardware working at mmWave radio frequency centred at 28.5GHz with 2GHz bandwidth. The baseband signal consists of in-phase (I) and quadrature (Q) components with a frequency range of –1GHz to 1GHz. A single Nyquist ADC samples the baseband signal at a 3.072GSps rate at the receiver.

Using NI LabVIEW development tools, the behaviour of the sub-Nyquist sampler can be simulated by pretreatments on Nyquist samples. The recovery algorithms implemented on the host controller process the real-time signal captured through the PCIe bus from the data acquisition card. An example implementation for reference is shown in [9]. Sample codes in MATLAB and data sets can be downloaded on the challenge website.

7 Challenge registration

The entrance for signing up for the challenge and submitting entries can be found at the Gbsense website. After registration, the data sets and the sample codes can be downloaded freely. The time nodes, awards and copyright rules are also announced

1) Participants may choose between MATLAB and Python, but LabVIEW code is necessary.

on the website. Participants will win 10,000 USD for the first prize, 5,000 USD for the second prize, and 3,000 USD for the third prize.

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References

1. Eldar Y C. Sampling Theory: Beyond Bandlimited Systems. Cambridge University Press, 2015
2. Tropp J A, Laska J N, Duarte M F, Romberg J K, Baraniuk R G. Beyond Nyquist: efficient sampling of sparse bandlimited signals. IEEE Transactions on Information Theory, 2009, 56(1): 520–544
3. Wakin M, Becker S, Nakamura E, Grant M, Sovero E, Ching D, Yoo J, Romberg J, Emami-Neyestanak A, Candes E. A nonuniform sampler for wideband spectrally-sparse environments. IEEE Journal on Emerging & Selected Topics in Circuits & Systems, 2012, 2(3): 516–529
4. Mishali M, Eldar Y C. From theory to practice: sub-Nyquist sampling of sparse wideband analog signals. IEEE Journal of Selected Topics in Signal Processing, 2010, 4(2): 375–391
5. Cohen D, Tsiper S, Eldar Y C. Analog-to-digital cognitive radio: sampling, detection, and hardware. IEEE Signal Processing Magazine, 2018, 35(1): 137–166
6. Mishali M, Eldar Y C, Dounaevsky O, Shoshan E. Xampling: analog to digital at sub-Nyquist rates. Circuits Devices & Systems Iet, 2009, 5(1): 8–20
7. Israeli E, Tsiper S, Cohen D, Shoshan E, Hilgendorf R, Reysenson A, Eldar Y C. Hardware calibration of the modulated wideband converter. In: Proceedings of 2014 IEEE Global Communications Conference. 2014, 948–953
8. Yoo J, Becker S, Loh M, Monge M, Emami-Neyestanak A. A 100MHz–2GHz 12.5x sub-Nyquist rate receiver in 90nm CMOS. In: Proceedings of Radio Frequency Integrated Circuits Symposium. 2012
9. Song Z, Qi H, Gao Y. Real-time multi-gigahertz sub-Nyquist spectrum sensing system for mmwave. In: Proceedings of the 3rd ACM Workshop on Millimeter-wave Networks and Sensing Systems. 2019, 33–38
10. Candes E J, Romberg J K, Tao T. Stable signal recovery from incomplete and inaccurate measurements. Communications on Pure and Applied Mathematics: a Journal Issued by the Courant Institute of Mathematical Sciences, 2006, 59(8): 1207–1223
11. Palomar D P, Eldar Y C. Convex Optimization in Signal Processing and Communications. Singapo Cambridge University Press, 2010
12. Zhang X, Ma Y, Gao Y, Zhang W. Autonomous compressive-sensing-augmented spectrum sensing. IEEE Transactions on Vehicular Technology, 2018, 67(8): 6970–6980
13. Tropp J A, Gilbert A C. Signal recovery from random measurements via orthogonal matching pursuit. IEEE Transactions on Information Theory, 2007, 53(12): 4655–4666
14. Tropp J A, Gilbert A C, Strauss M J. Simultaneous sparse approximation via greedy pursuit. In: Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing. 2005, 721–724
15. Needell D, Tropp J A. Cosamp: iterative signal recovery from incomplete and inaccurate samples. Applied and Computational Harmonic Analysis, 2009, 26(3): 301–321
16. Qi H, Zhang X, Gao Y. Low-complexity subspace-aided compressive spectrum sensing over wideband whitespace. IEEE Transactions on Vehicular Technology, 2019, 68(12): 11762–11777
17. Eldar Y C, Kuppinger P, Bolcskei H. Block-sparse signals: uncertainty relations and efficient recovery. IEEE Transactions on Signal Processing, 2010, 58(6): 3042–3054
18. Chen W, Wassell I J. A decentralized bayesian algorithm for distributed compressive sensing in networked sensing systems. IEEE Transactions on Wireless Communications, 2015, 15(2): 1282–1292
19. Urkowitz H. Energy detection of unknown deterministic signals. Proceedings of the IEEE, 1967, 55(4): 523–531
20. Tandra R, Sahai A. SNR walls for signal detection. IEEE Journal of Selected Topics in Signal Processing, 2008, 2(1): 4–17
21. Kim K, Xin Y, Rangarajan S. Energy detection based spectrum sensing for cognitive radio: an experimental study. In: Proceedings of 2010 IEEE Global Telecommunications Conference GLOBECOM 2010. 2011
22. Oner M, Jondral F. Cyclostationarity-based methods for the extraction of the channel allocation information in a spectrum pooling system. In: Proceedings of 2004 IEEE Radio and Wireless Conference. 2004, 279–282
23. Cohen D, Eldar Y C. Sub-Nyquist cyclostationary detection for cognitive radio. IEEE Transactions on Signal Processing, 2017, 65(11): 3004–3019
24. Qin Z, Zhou X, Zhang L, Gao Y, Liang Y C, Li G Y. 20 years of evolution from cognitive to intelligent communications. IEEE Transactions on Cognitive Communications and Networking, 2019, 6(1): 6–20
25. Toma A, Krayani A, Farrukh M, Qi H, Marcenaro L, Gao Y, Regazzoni C S. AI-based abnormality detection at the PHY-layer of cognitive radio by learning generative models. IEEE Transactions on Cognitive Communications and Networking, 2020, 6(1): 21–34
26. Thilina K M, Choi K W, Saquib N, Hossain E. Machine learning techniques for cooperative spectrum sensing in cognitive radio networks. IEEE Journal on Selected Areas in Communications, 2013, 31(11): 2209–2221
27. Hu H, Wang Y, Song J. Signal classification based on spectral correlation analysis and SVM in cognitive radio. In: Proceedings of the 22nd International Conference on Advanced Information Networking and Applications. 2008, 883–887
28. Naparstek O, Cohen K. Deep multi-user reinforcement learning for distributed dynamic spectrum access. IEEE Transactions on Wireless Communications, 2018, 18(1): 310–323
29. Zhang Y, Wan P, Zhang S, Wang Y, Li N. A spectrum sensing method based on signal feature and clustering algorithm in cognitive wireless multimedia sensor networks. Advances in Multimedia, 2017
30. Malafaia D, Vieira J, Tomé A. Adaptive threshold spectrum sensing based on expectation maximization algorithm. Physical Communication, 2016, 21: 60–69
31. Boufounos P, Duarte M F, Baraniuk R G. Sparse signal reconstruction from noisy compressive measurements using cross validation. In : Proceedings of the 14th IEEE/SP Workshop on Statistical Signal Processing. 2007, 299–303
32. Wang Y, Tian Z, Feng C. Sparsity order estimation and its application in compressive spectrum sensing for cognitive radios. IEEE Transactions on Wireless Communications, 2012, 11(6): 2116–2125

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