Sub-Nyquist spectrum sensing and learning challenge

Yue GAO (✉) 1, Zihang SONG 1, Han ZHANG 1, Sean FULLER 2, Andrew LAMBERT 3, Zhinong YING 4, Petri MÄHÖNEN 5, Yonina ELDAR 6, Shuguang CUI 7, Mark D. PLUMBLEY 1, Clive PARINI 8, Arumugam NALLANATHAN 8

1 School of Computer Science and Electronic Engineering, University of Surrey, Guildford, Surrey GU2 7XH, UK
2 National Instruments Corporation (UK) Ltd, Newbury, Berkshire RG14 2PZ, UK
3 Electronic Media Services Ltd, Bordon, Hampshire GU35 0FJ, UK
4 Sony Research Center, Sony Corporation, Lund 221 88, Sweden
5 Institute for Networked Systems, RWTH Aachen University, Kackertstrasse 9, Aachen 52072, Germany
6 Faculty of Math & CS, Weizmann institute of Science, Rehovot 7610001, Israel
7 School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen 518172, China
8 School of Electronic Engineering and Computer Science, Queen Mary University of London, London E1 4NS, UK

© The Author(s) 2021. This article is published with open access at link.springer.com and journal.hep.com.cn

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
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 500–600000raw 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.

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.

---

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

---

Table 1 Criteria for evaluating the entries

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

\(^1\) 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.

Acknowledgements The challenge was sponsored by National Instruments (NI) Corp. and the Engineering and Physical Sciences Research Council (EPSRC) under the Grant EP/R00711X/2, United Kingdom.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made.

The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

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, Reysensson 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. Candès 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, Boleskei 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 networking 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, Pan 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
Yue Gao is a Professor and Chair in Wireless Communications at Institute for Communication Systems, School of Computer Science and Electronic Engineering, University of Surrey, UK. He received a PhD degree from the Queen Mary University of London, UK. He leads the Antennas and Signal Processing Lab developing fundamental research in practice in the interdisciplinary area of smart antennas, signal processing, spectrum sharing, millimeterwave, and Internet of Things technologies in mobile and satellite systems. He has published over 200 peer-reviewed journal and conference papers, one book and five book chapters. He is an Engineering and Physical Sciences Research Council Fellow from 2018 to 2023. He was a co-recipient of the EU Horizon Prize Award on Collaborative Spectrum Sharing in 2016.

Zhilong Song received his bachelor’s and master’s degrees in Applied Physics from Beihang University, China. He started his PhD study in 2019 and is now with Prof. Yue Gao and Prof. Rahim Tafazolli in University of Surrey, UK. His current research interests include millimetre-wave spectrum sensing and sub-Nyquist signal processing.

Han Zhang received his PhD degree in Electrical and Electronics Engineering from University of California, Davis, Davis, California, USA, in 2019. He is currently working as a research assistant in the University of Surrey, UK. His research interests include utilizing data driven methods on telecommunication scenarios, such as transceiver design and compressive sensing.

Sean Fuller is a Senior Account Manager at NI, specialised in wireless communications, data acquisition, and data analytics. He focuses on fostering collaborative relationships between industry and academia, with the goal of accelerating innovation. He received his Bachelor of Engineering (Hons) from the University of Portsmouth, UK.

Andrew Lambert (CEng FIET MIoD, Founder and CEO of Electronic Media Services Ltd and Founder and COO of Fibre Ltd) is a Chartered Engineer and Fellow of the Institution of Engineering Technology. He is an experienced board-level executive with a proven record of developing new technology to solve business problems with extensive practical experience of working in Europe and Asia.

Zhinong Ying is a principle researcher of Antenna technology in the Network Technology Lab within the Research Centre, Sony Cooperation, Sweden, also as a distinguish engineer within the whole Sony group. He joined Ericsson AB in 1995 in Sweden. He became Senior Specialist in 1997 and Expert in 2003 in his engineer career at Ericsson. He has also been a part time professor in department of electronic system, Aalborg University, Denmark since 2021. He is a Fellow of IEEE. He was a member of scientific board of ACE program (Antenna Centre of Excellent in European 6th frame) from 2004 to 2007.

Petri Mähönen is currently a Full Professor and the Chair of Networked Systems with RWTH Aachen University, Germany. His current research interests include cognitive radio systems, embedded intelligence, and future wireless networks architectures, including millimeter-wave systems and techno-economics especially from a regulatory perspective. He is also serving as an Editor for the IEEE Transactions on Wireless Communications. He is also co-recipient of IEEE Jack Neubauer Memorial Award and received Telekom Research Prize for his work on spectrum related research.

Yonina Eldar is a Professor in the Department of Mathematics and Computer Science, Weizmann Institute of Science, Israel, where the heads the center for biomedical engineering. She was previously a Professor in the Department of Electrical Engineering at the Technion, where she held the Edwards Chair in Engineering. She is also a Visiting Professor at MIT, a Visiting Scientist at the Broad Institute, and an Adjunct Professor at Duke University and was a Visiting Professor at Stanford. She is a member of the Israel Academy of Sciences and Humanities, an IEEE Fellow and a EURASIP Fellow. She is the Chief Editor of Foundations and Trends in Signal Processing and a member of several IEEE Technical Committees and Award Committees.

Shuguang Cui received his PhD from Stanford in 2005. He is now a Chair Professor at The Chinese University of Hong Kong (Shenzhen), China. His current research interest is data driven large-scale information analysis and system design. He was selected as the Thomson Reuters Highly Cited Researcher and listed in the Worlds’ Most Influential Scientific Minds by Sciencewatch in 2014. He was the recipient of the IEEE Signal Processing Society 2012 Best Paper Award. He is an IEEE Fellow and ComSoc Distinguished Lecturer.

Mark D. Plumbley is Professor of Signal Processing at the Centre for Vision, Speech and Signal Processing (CVSSP) and Head of School of Computer Science and Electronic Engineering at the University of Surrey, in Guildford, UK. He is an expert on analysis and processing of audio, using a wide range of signal processing and machine learning methods. He led the first international data challenge on Detection and Classification of Acoustic Scenes and Events (DCASE 2013), and is a co-editor of the recent book on “Computational Analysis of Sound Scenes and Events” (Springer, 2018). He currently holds a 5-year EPSRC Fellowship on “AI for Sound”, aiming to bring sound recognition technology “out of the lab” for the benefit of society.
Clive Parini joined Queen Mary as Lecturer in 1977, promoted to Reader in 1990, promoted to Professor in 1999 and is currently Professor of Antenna Engineering and heads the Antenna & Electromagnetics Research Group. He has published over 400 papers on research topics including array mutual coupling, array beam forming, antenna metrology, microstrip antennas, millimetrewave compact antenna test ranges, millimetrewave integrated antennas, metamaterials and on-body communications. He is a Fellow of the IET and a past member and Chairman of the IET Antennas & Propagation Professional Network Executive Team. He is a past member of the editorial board and past Honorary Editor for the IET Journal Microwaves, Antennas & Propagation. In 2009 he was elected a Fellow of the Royal Academy of Engineering.

Arumugam Nallanathan is Professor of Wireless Communications and the founding head of the Communication Systems Research (CSR) group in the School of Electronic Engineering and Computer Science at Queen Mary University of London, UK since September 2017. He was with the Department of Informatics at King’s College London from December 2007 to August 2017, where he was Professor of Wireless Communications. He was an Assistant Professor in the Department of Electrical and Computer Engineering, National University of Singapore from August 2000 to December 2007. He has been selected as a Web of Science (ISI) Highly Cited Researcher in 2016. He is an IEEE Fellow and IEEE Distinguished Lecturer.