Editorial: Introduction to the Special Issue on Deep Learning for High-Dimensional Sensing

I. Introduction

WE LIVE in a high-dimensional world and sensing is the first step to perceive and understand the environment for both human beings and machines. Therefore, high-dimensional sensing (HDS) plays a pivotal role in many fields such as robotics, signal processing, computer vision and surveillance. The recent explosive growth of artificial intelligence has provided new opportunities and tools for HDS, especially for machine vision. In many emerging real applications such as advanced driver assistance systems/autonomous driving systems, large-scale, high-dimensional and diverse types of data need to be captured and processed with high accuracy and in a real-time manner. Bearing this in mind, now is the time to develop new sensing and processing techniques with high performance to capture high-dimensional data by leveraging recent advances in deep learning (DL). Accordingly, this special issue (SI) of IEEE Journal of Selected Topics in Signal Processing (J-STSP) is dedicated to DL for HDS.

Although it is challenging to provide an overview of recent advances in DL for HDS due to the richness of this topic, we are excited to see various directions in this SI, including new spectral imaging systems, datasets and algorithms, low-light and RGB-D imaging systems, compressive sensing magnetic resonance imaging (CS-MRI) inversion algorithms, action recognition, multi-modal learning, fingerprints recognition, radar detection, Lidar and surveillance sensing and analysis. In the following, we give a brief introduction to the papers that comprise the present SI.

II. Summary of the SI

Real scenes are spectrally rich and it is demanding to capture high-resolution spectral images including multispectral and hyperspectral images. Towards this end, different techniques have been proposed in the literature. Among these methods, the snapshot spectral imaging approach stands out due to its high temporal resolution.

In this era of deep learning, large datasets are desired to train deep neural networks. However, for a long time, high quality datasets have been in short supply. To address this challenge, *Erqi Huang, Maoqi Zhang, Zhan Ma, Linsen Chen, Yiyu Zhuang and Xun Cao* built a snapshot-scanning spectral system to capture snapshot measurements of the physical world and corresponding high spatio-spectral scanned ground-truths simultaneously [A1]. A computational hyperspectral image light dataset including both physical-world measurement and ground truth is published. We hope this dataset can serve as a baseline for training DL models, a test bed for different algorithms.

To capture multispectral images, one solution is to use a pseudo-panchromatic camera with a multispectral array. In [A2], *Shumin Liu, Yuge Zhang, Jie Chen, Keng Pang Lim and Susanto Rahardja* proposed a deep joint network for multispectral demosaicking. Taking one step further, *Tao Zhang, Zhiyuan Liang and Ying Fu* proposed a method for snapshot spectral imaging using joint spatial-spectral pattern optimization and deep unfolding networks to reconstruct hyperspectral images from the compressed measurement [A3].

Another method to achieve high-resolution hyperspectral images is to capture a pair of images of the same scene, one with low spectral-resolution but high spatial-resolution and the other one with high spectral-resolution but low spatial-resolution. Following this, a fusion algorithm is required to merge these two images to obtain a final image with both high spatial and high spectral resolutions. Towards this end, *Ruiying Lu, Bo Chen, Jianqiao Sun, Wenchao Chen, Penghui Wang, Yuanwei Chen, HongWei Liu and Pramod K. Varshney* proposed a heterogeneity-aware recurrent neural network, leading to excellent results [A4]. In [A5], *Wujie Zhou, Jianhui Jin, Jingsheng Lei and Lu Yu* proposed a cross-layer interaction and multiscale fusion network for semantic segmentation of high-resolution remote sensing images. Aiming to improve the segmentation accuracy for RGB-D scene parsing, a feature reconstruction network was proposed by *Wenjia Zhou, Enquan Yang, Jingsheng Lei and Lu Yu* in [A6].

Coded aperture compressive imaging provides a unique way to sample high-dimensional data including hyperspectral images and videos, which can provide high resolutions in the spatial, spectral, temporal domains simultaneously. Based on this idea, in [A7], *Miguel Marquez, Yingming Lai, Xianglei Liu, Cheng Jiang, Shian Zhang, Henry Arguello and Jinyang Liang* proposed an end-to-end convolutional neural network that offers multi-faceted supervision for snapshot compressive imaging by optimizing the coded aperture, sensing the shearing operation, and reconstructing three-dimensional datacubes. The proposed DL networks were applied to hyperspectral and ultra high-speed compressive imaging systems. Related to high-speed imaging, in [A8], a new method were proposed by *Daoyu Li, Liheng Bian and Jun Zhang* to sample high-speed large-scale images using frame decomposition with motion-inherent multiplexing.

Date of current version July 11, 2022.
Digital Object Identifier 10.1109/JSTSP.2022.3185190

Compressive sensing has a wide range of applications in MRI. There are two main issues in CS-MRI: one is the sampling pattern design and the other is the reconstruction algorithm. Similar to other inverse problems, deep learning has shown significant superiority in CS-MRI image recovery. To this end, in [A9], *Filippo Martinini, Mauro Mangia, Alex Marchioni, Riccardo Rovatti and Gianluca Setti* proposed a deep learning method, specifically a new loss function plus a post-processing step, for optimal under-sampling patterns and image recovery for MRI. In [A10], *Yilang Zhang, Xiaojun Mao, Jian Wang and Weidong Liu* proposed a deartifacting module that can effectively remove artifacts by eliminating sparse outliers in the k-space. In [A11], *Jingfen Xie, Jian Zhang, Yongbing Zhang and Xiangyang Ji* proposed a probabilistic under-sampling and reconstruction network to jointly optimize the sampling pattern and the reconstruction network in CS-MRI. The sampling subnet explores an optimal probabilistic sub-sampling pattern that describes independent Bernoulli random variables at each possible sampling point, retaining robustness and stochastics for more reliable CS reconstruction. As deep unfolding has been a main trend for inverse network design, in [A12], *Jian Zhang, Zhenyu Zhang, Jingfen Xie and Yongbing Zhang* compared different deep unfolding networks for CS-MRI, providing guidance for network design.

Due to the powerful performance of deep unfolding/unrolling network, *Jakeoung Koo, Abderrahim Halimi and Stephen McLaughlin* combined deep unrolling algorithm with statistical Bayesian architecture for robust image reconstruction from single-photon Lidar data [A13].

Similarly, by integrating Bayesian learning with DL, in [A14], a deep probabilistic model for high range resolution (HRR) Radar signal and its application in target recognition was proposed by *Leiyao Liao, Lan Du and Jian Chen*. In detail, based on the radar target scattering center model which describes the HRR radar signal as the summation of echoes from the scattering center, a deep probabilistic model is constructed to depict the generative process from the scattering center to observation, where the latent features comprise location and intensity of scattering center.

Also using DL for radar but at 77 GHz mmWave, *Xiangyu Gao, Hui Liu, Sumit Roy, Guanbin Xing, Ali Alansari, and Youchen Luo* focused on the carried object detection problem using a low-cost radar system [A15]. The proposed system is capable of real-time detection of objects such as laptops, mobile phones, and knives, in open suitcases and concealed suitcases where objects are hidden in clothes or bags.

In line with the development of electromagnetic world, but for another task, *Aichun Zhu, Zhonghua Tang, Zixuan Wang, Yue Zhou, Shichao Chen, Fangqiang Hu and Yifeng Li* proposed an attentional temporal convolutional network for human action prediction using WiFi channel state information in [A16]. It is worth noting that a dataset for human action prediction was also built in this work.

Fingerprint detection, a widely used technique, has also been enhanced by DL. In [A17], *Chengsheng Yuan, Peipeng Yu, Zhihua Xia, Xingming Sun, and Q. M. Jonathan Wu* exploited the relationship of spatial ridges in fingerprints and proposed a novel fingerprint living detection method based on the continuity of spatial ridges.

Let us come back to the imaging part, in which low-light vision has been a longstanding challenge. To address this, in [A18], *Peiyao Guo, M. Salman Asif and Zhan Ma* built a dual-camera system composed of a high spatial resolution monochromatic image and a low spatial resolution color image; DL networks were proposed to synthesize these two images to generate a high-resolution color image in low-light environment.

Instead of focusing on one type of data, DL enables multimodality learning. In [A19], *Shi Mao, Mengqi Ji, Bin Wang, Qionghai Dai and Lu Fang* proposed a surface material perception method by using multimodal learning of structured laser spots captured by a depth camera. Specifically, the authors decompose the captured active infrared image into diffuse and dot modals and reveal their connection to optical properties such as reflection and scattering of different materials. In [A20], *Chengchao Wang, Rencan Nie, Jinde Cao, Xue Wang, and Ying Zhang* proposed an unsupervised information gated network for multimodal medical images fusion.

Last but not least, surveillance is an important application of HDS. In [A21], *Varun K. Garg and Thanuka L. Wickramarathne* proposed a DL approach for enhancing situational awareness in surveillance applications with ubiquitous HDS, which makes strong echos to our main theme of this SI.

III. Outlook

As can be seen from the above works on diverse topics, deep learning has revolutionized a number of fields and is now a common tool for various tasks. Now is the time to think about the next step of high dimensional sensing. While previous researches on high dimensional sensing have been focusing on the 'sampling' part, the final goal of sensing is usually to accomplish some tasks rather than capture some data. Therefore, task-driven sensing is a good research direction and needs more attention. Also, how to integrate deep learning, especially Transformers into the sensing process is a research direction that deserves more efforts.

Acknowledgment

We would like to thank all authors who submitted their papers to this issue. Our guest editors would also like to express our sincere gratitude to all reviewers.

Xin Yuan, *Lead Guest Editor*
School of Engineering
Westlake University
Hangzhou, Zhejiang 310030, China

David J. Brady, *Guest Editor*
College of Optical Sciences
University of Arizona
Tucson, AZ 85719, USA

Jinli Suo, *Guest Editor*
Department of Automation
Tsinghua University
Beijing 100084, China

HENRY ARGUELLO, *Guest Editor*
Department of System Engineering and Informatics
Universidad Industrial de Santander
Bucaramanga 680002, Colombia

MIGUEL RODRIGUES, *Guest Editor*
Department Electronic and Electrical Engineering
University College London
WC1E 7JE London, U.K.

AGGELOS K. KATSAGGELOS, *Guest Editor*
Department of Electrical and Computer Engineering
Northwestern University
Evanston, IL 60208, USA

APPENDIX
RELATED ARTICLES

[A1] E. Huang, M. Zhang, Z. Ma, L. Chen, Y. Zhuang, and X. Cao, "High-fidelity hyperspectral snapshot of physical world: System architecture, dataset and model," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3167891.

[A2] S. Liu, Y. Zhang, J. Chen, L. K. Pang, and S. Rahardja, "A deep joint network for multispectral demosaicking based on pseudo-panchromatic images," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3172865.

[A3] T. Zhang, Z. Liang, and Y. Fu, "Joint spatial-spectral pattern optimization and hyperspectral image reconstruction," *IEEE J. Sel. Top. Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3179806.

[A4] R. Lu, *et al.*, "Heterogeneity-aware recurrent neural network for hyperspectral and multispectral image fusion," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3180896.

[A5] W. Zhou, J. Jin, J. Lei, and L. Yu, "CIMFNet: Cross-layer interaction and multiscale fusion network for semantic segmentation of high-resolution remote sensing images," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3159032.

[A6] W. Zhou, E. Yang, J. Lei, and L. Yu, "FRNet: Feature reconstruction network for RGB-D indoor scene parsing," *IEEE J. Sel. Topics Signal Process.*, early access, May 12, 2022, doi: 10.1109/JSTSP.2022.3174338.

[A7] M. Marquez *et al.*, "Deep-learning supervised snapshot compressive imaging enabled by an end-to-end convolutional neural network," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3172592.

[A8] D. Li, L. Bian, and J. Zhang, "High-speed large-scale imaging using frame decomposition from intrinsic multiplexing of motion," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3164524.

[A9] F. Martinini, M. Mangia, A. Marchioni, R. Rovatti, and G. Setti, "A deep learning method for optimal undersampling patterns and image recovery for MRI exploiting losses and projections," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3171082.

[A10] Y. Zhang, X. Mao, J. Wang, and W. Liu, "DEMO: A flexible deartifacting module for compressed sensing MRI," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3158057.

[A11] J. Xie, J. Zhang, Y. Zhang, and X. Ji, "PUERT: Probabilistic under-sampling and explicable reconstruction network for CS-MRI," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3170654.

[A12] J. Zhang, Z. Zhang, J. Xie, and Y. Zhang, "High-throughput deep unfolding network for compressive sensing MRI," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3170227.

[A13] J. Koo, A. Halimi, and S. Mclaughlin, "A Bayesian based deep unrolling algorithm for single-photon lidar systems," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3170228.

[A14] L. Liao, L. Du, and J. Chen, "Interpretable deep probabilistic model for HRR radar signal and its application to target recognition," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3160241.

[A15] X. Gao, H. Liu, S. Roy, G. Xing, A. Alansari, and Y. Luo, "Learning to detect open carry and concealed object with 77 GHz radar," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3171168.

[A16] A. Zhu *et al.*, "Wi-ATCN: Attentional temporal convolutional network for human action prediction using WiFi channel state information," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3163858.

[A17] C. Yuan, P. Yu, Z. Xia, X. Sun, and Q. M. J. Wu, "FLD-SRC: Fingerprint liveness detection for AFIS based on spatial ridges continuity," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3174655.

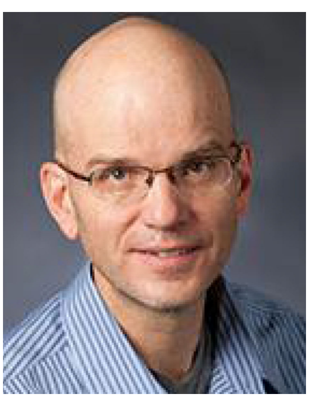
[A18] P. Guo, M. S. Asif, and Z. Ma, "Low-light color imaging via cross-camera synthesis," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3175015.

[A19] S. Mao, M. Ji, B. Wang, Q. Dai, and L. Fang, "Surface material perception through multimodal learning," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3171682.

[A20] C. Wang, R. Nie, J. Cao, X. Wang, and Y. Zhang, "IGNFusion: An unsupervised information gate network for multimodal medical images fusion," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3181717.

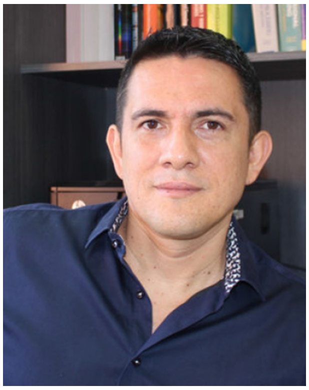
[A21] V. K. Garg and T. L. Wickramarathne, "A deep-learning approach for enhancing situational awareness in surveillance applications with ubiquitous high-dimensional sensing," *IEEE J. Sel. Topics Signal Process.*, vol. 16, no. 4, Jun. 2022, doi: 10.1109/JSTSP.2022.3184174.

Xin Yuan (Senior Member, IEEE) received the Ph.D. degree from Hong Kong Polytechnic University, Hong Kong, in 2012. From 2012 to 2015, he was a Postdoctoral Associate with the Department of Electrical and Computer Engineering, Duke University, Durham, NC, USA, where he was working on compressive sensing and machine learning. From 2015 to 2021, he was a video analysis and coding lead Researcher with Bell Labs, Murray Hill, NJ, USA. He is currently an Associate Professor with Westlake University, Hangzhou, China. He has authored or coauthored more than 150 journal and conference papers, and holds more than 20 international patents. His research interests include computational imaging, machine learning, and signal processing. Since 2019, he has been the Associate Editor of *Pattern Recognition*.



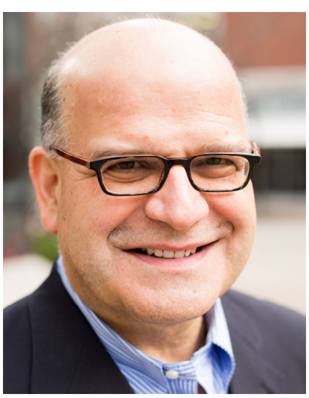
David J. Brady (Fellow, IEEE) received the graduation degree from Macalester College, St Paul, MN, USA, and Caltech, Pasadena, CA, USA. He is currently the J.W. and H.M. Goodman Chair of optical sciences with the University of Arizona, Tucson, AZ, USA. He was a Professor of electrical and computer engineering with Duke University, Durham, NC, USA, and Duke Kunshan University, Suzhou, China. He was on the Faculty of the University of Illinois, Champaign, IL, USA. He is the author of *Optical Imaging and Spectroscopy*. His research interests include array cameras and compressive tomography. He is a Fellow of OSA and SPIE. He won the 2013 SPIE Dennis Gabor Award for work on compressive holography.

Jinli Suo received the B.S. degree in computer science from Shandong University, Jinan, China, in 2004, and the Ph.D. degree from the Graduate University of Chinese Academy of Sciences, Beijing, China, in 2010. She is currently an Associate Professor with the Department of Automation, Tsinghua University, Beijing, China. Her research interests include computer vision, computational photography, and statistical learning.



Henry Arguello (Senior Member, IEEE) received the B.Sc. Eng. degree in electrical engineering, the M.Sc. degree in electrical power from the Universidad Industrial de Santander, Bucaramanga, Colombia, in 2000 and 2003, respectively, and the Ph.D. degree in electrical engineering from the University of Delaware, Newark, DE, USA, in 2013. He is currently an Associate Professor with the Department of Systems Engineering, Universidad Industrial de Santander. In first semester 2020, he was a Visiting Professor with Stanford University, Stanford, CA, USA, funded by Fulbright. His research interests include high-dimensional signal processing, optical imaging, compressed sensing, hyperspectral imaging, and CI.

Miguel Rodrigues (Senior Member, IEEE) received the Licenciatura degree in electrical and computer engineering from the University of Porto, Porto, Portugal, and the Ph.D. degree in electronic and electrical engineering from the University College London (UCL), London, U.K. He is currently a Professor of information theory and processing with UCL, and a Turing Fellow with the Alan Turing Institute, U.K. National Institute of Data Science and Artificial Intelligence. His work has led to more than 200 articles in leading journals and conferences in the field, a book on *Information-Theoretic Methods in Data Science* (Cambridge University Press). His research interests include information theory, information processing, and machine learning. He was recipient of the IEEE Communications and Information Theory Societies Joint Paper Award 2011.



Aggelos K. Katsaggelos (Fellow, IEEE) received the diploma degree in electrical and mechanical engineering from the Aristotelian University, Thessaloniki, Greece, in 1979, and the M.S. and Ph.D. degrees in electrical engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 1981 and 1985, respectively. He is currently a Professor of electrical and computer engineering (courtesy computer science), holder of the Joseph Cummings Chair with Northwestern University, Evanston, IL, USA. He has authored or coauthored seven books, more than 300 journal papers, 600 conference papers, 40 book chapters, and 30 international patents, in the areas of multimedia signal processing and communications, computational imaging, and machine learning. He is a Fellow of SPIE, OSA, and EURASIP.