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

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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 pivotal roles 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 / automated 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, it is now the time to develop new sensing and processing techniques with high performance to capture high-dimensional data employing recent advances in deep learning (DL). Accordingly, this special issue (SI) on IEEE Journal of Selected Topics in Signal Processing (J-STSP) is devoted to DL for HDS.

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Although it is challenging to provide an overview of recent advances of DL for HDS due to the richness of this topic, we are exciting 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-modality 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 spectral 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. Within these methods, snapshot spectral imaging approach stands out due to the advantage of 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 are 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 the snapshot measurements of physical world and corresponding high spatio-spectral scanned ground-truths simultaneously [1]. 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 to train DL models, a test bed of different algorithms, etc.

To capture multispectral images, one solution is to use the pseudo-panchromatic camera with a multispectral array. In [2], *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 using joint spatial-spectral pattern optimization for snapshot spectral imaging and the use deep unfolding networks to reconstruct the hypersepectral images from the compressed measurement [3].

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 [4]. In [5], *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 [6].

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 [7], *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 to 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 [8], a new method were proposed by *Daoyu Li, Liheng Bian and Jun Zhang* to sample high-speed large-scale images using frame decomposition from intrinsic multiplexing of motion.

Compressive sensing has vast applications in MRI. There are two main issues in CS-MRI: one is the sampling pattern design and the other one is the reconstruction algorithm. Similar to other inverse problems, deep learning has shown significant superiority in CS-MRI image recovery. To this end, in [9], *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 [10], *Yilang Zhang, Xiaojun Mao, Jian Wang and Weidong Liu* proposed a deartifacting module that can effectively remove the artifacts by eliminating sparse outliers in the k-space. In [11], *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, which describes independent Bernoulli random variables at each possible sampling point, thus retaining robustness and stochastics for a more reliable CS reconstruction. As deep unfolding has been a main trend for inverse network design, in [12], *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* combinined deep unrolling algorithm with statistical Bayesian architecture for robust image reconstruction from single-photon Lidar data [13].

Similarly, by connecting Bayesian learning with DL, in [14], a deep probabilistic model for high range resolution (HRR) Radar signal and its application to target recognition was proposed by *Leiyao Liao, Lan Du and Jian Chen*. In detail, based on the radar targets scattering center model which describes the HRR radar signal as the summation of echoes from the scattering centers, a deep probabilistic model is constructed to depict the generative process from the scattering centers to observations, where the latent features comprise the locations and strength of scattering centers.

Also using DL for radar but at 77GHz mmWave, *Xiangyu Gao, Hui Liu, Sumit Roy, Guanbin Xing, Ali Alansari, and Youchen Luo* focused on the carried objects detection problem using a low-cost radar system [15]. The proposed system is capable of real-time detecting objects such as laptop, phone, and knife, under open carry and concealed cases where objects are hidden with 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 [16]. 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 [17], *Chengsheng Yuan, Peipeng Yu, Zhihua Xia, Xingming Sun, and Q. M. Jonathan Wu* exploited the relationship of spatial ridges in fingerprints and propose a novel fingerprint liveness detection method based on spatial ridges continuity.

Let us come back to the imaging part, in which low-light vision has been a long term challenge. To address this, in [18], *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 the two images, leading to a high-resolution color image in low-light environment.

Instead of focusing on one type of data, DL enables multi-modality learning. In [19], *Shi Mao, Mengqi Ji, Bin Wang, Qionghai Dai and Lu Fang* proposed a surface material perception method through multimodal learning using a depth camera shooting structured laser dots. Specifically, the authors decompose the captured active infrared image into diffuse and dot modals and reveal their connection with different material optical properties such as reflection and scattering. In [20], *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 [21], *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 for diverse topics, deep learning has revolutionized a number of fields and is now a common tool for various tasks. Now it is the time to think about the next step of high dimensional sensing. While previous researches of high-dimensional sensing have been focusing the 'sampling' part, the final goal of sensing is usually to finish 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 the convolutional neural networks such as Transformers into the sensing process is a research direction that deserves more efforts.

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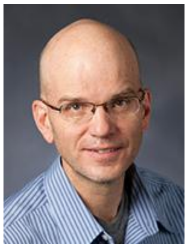

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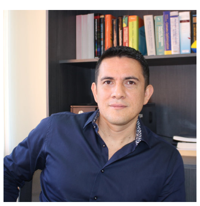

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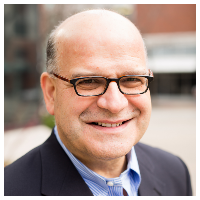

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