Special Section Guest Editorial: Advances in High-Dimensional Medical Image Processing

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When we proposed this *Journal of Medical Imaging* (JMI) Special Section around the analysis of high-dimensional medical imaging data, we envisioned bringing together diverse approaches for extracting meaningful information in the context of the underlying clinical problems or healthcare applications. We were particularly interested in exploring the state-of-the-art of algorithms that spanned multiple imaging modalities including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), single-photon emission computerized tomography (SPECT), ultrasound, macroscopic, and microscopic imaging, as well as a combination of image and non-image data. The first use of terms "high-dimensional" and "medical image processing" that we could identify was in 1980 by Tsuji and Yachida,[1] who described an efficient analysis of moving images in medicine and biology. In this study, the authors proposed a system for analyzing consecutive image frames of heart wall motion by utilizing both *a priori* and acquired knowledge to extract significant and useful information at a low computational cost to solve their high-dimensional, nonserial optimization problem.[1] Interestingly, the first deep learning paper referencing our theme was a technical report from 1992 by McCoy and Ersoy,[2] who implemented a three-layered artificial neural network on commodity programmable hardware with an impressive 8 input, 8 hidden, and 8 output nodes at a reported cost of ∼$3500 (∼$7000 in 2022 when compensating for inflation).

Much has changed in the past four decades. Through our SPIE Medical Imaging: Image Processing program committee, we have seen immense innovation in classification, segmentation, registration, modeling, visualization, augmented/virtual reality using model-based analysis, and artificial intelligence approaches.[3] The articles in this Special Section cover a gamut of analysis approaches and target applications. Couvy-Duchesne et al. used advanced linear mixed models (LMMs) to account for the covariance of gray-matter measurements among multiple brain regions extracted from MRI images.[4] These underrecognized techniques become quite important in the context of large studies, for example, as shown with 8,662 subjects from the UK BioBank. Yao et al. developed a whole-slide imaging (WSI) technique for segmenting glomeruli that did not use traditional "high-quality" expert-labeled data, which are scarce and costly.[5] Rather, the authors showed that it is possible to develop efficient medical image processing algorithms using only data that are found from publicly accessible web image searches. In addition, their algorithms as well as the 30,000 web-mined glomerular images have been made publicly available. Noothout et al. explored the distillation of ensemble learning architectures into computationally efficient single convolutional networks.[6] Their work provides an approach for investigating the computational benefits of ensemble learning that was tested on four organs in chest CT scans, six structures in brain MRI, and three structures in cardiac cine-MRI. Yang et al. demonstrated an efficient deep learning-based segmentation of thigh and lower leg anatomy using low dose, single slice acquisition across a substantial cohort of 11,961 CT scans.[7] In a two-stage coarse-to-fine deep learning method, the authors first trained a network with approximate handcrafted segmentation labels, and then fine-tuned the trained model with human expert labels to improve the segmentation accuracy. Van Velzen et al. used adversarial learning to synthesize cardiac images without coronary artery calcium (CAC) to substantially improve the consistency over manual clinical calcium scoring.[8] Their approach demonstrated clear benefits of data-driven approaches over purely human-based reads on a large cohort of CT images from 1,662 patients. Saini and Mathur proposed a sparse representation dictionary learning approach for image fusion, which represents a promising approach for visualizing complex information that was evaluated by fusing MRI and PET, and MRI and SPECT brain images of glioma patients.[9] Finally, Agnes and Anitha proposed a multiscale convolutional neural network model for lung nodule segmentation from chest CT images.[10] In the proposed approach, feature fusion at fine and coarse scales is combined with a standard segmentation backbone, so as to achieve strong performance across a variety of nodule types and complexity levels.

While this Special Section was open for all submissions, we encouraged submissions from the SPIE Medical Imaging: Image Processing 2021 conference, the annual SPIE meeting that brings together researchers with interest in medical image processing, and is accompanied with topics in physics, computer-aided diagnosis, image-guided procedures and robotic interventions, image perception and observer performance, biomedical applications, healthcare imaging informatics, ultrasonic imaging and tomography, and digital and computational pathology as part of the main symposium. We received 14 submissions, out of which seven are published, and we look forward to seeing the field continue to advance with SPIE helping to bring together scholars to share their work, discuss emerging ideas, and form community.[3] In the interest of full disclosure, Ivana Išgum is a current co-chair of SPIE Medical Imaging: Image Processing, Bennett A. Landman is a past co-chair, and Tomaž Vrtovec serves on the program committee besides being an associate editor for JMI.

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