Highlights From RSNA 2017: Physics and Technology

By Robert Nishikawa, PhD, FSBI

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The quality and variety of breast imaging research presented at the 2017 Radiological Society of North America (RSNA) physics sessions were excellent. Here are selected highlights that I found personally interesting.

Let's start with a deep learning application. No, not one to find breast cancer in mammograms or distinguish benign from malignant lesions on ultrasound. There are many academic sites and companies working on those types of problems. Instead, this presentation focused on dose reduction and was entitled "Virtual High-Dose Technology: Radiation Dose Reduction in Digital Breast Tomosynthesis (DBT) by Means of Supervised Deep-Learning Image Processing." It was presented by Junchi Liu, who is a graduate student of Kenji Suzuki, PhD, at the Illinois Institute of Technology, in collaboration with Laurie Fajardo, MD, MBA, FACR, FSBI, a breast imager from Park City, Utah. In their work, they trained a neural network using the DBT projections of a cadaver breast embedded with simulated microcalcifications imaged at twice the clinical dose. They then input to the trained neural network DBT projection images taken at 20% of a clinical dose. The neural network was able to remove noise from the image and reconstruct the data to produce DBT slices that have noise properties similar to those of an image taken at 120% of the clinical dose. By training the neural network on a high-dose cadaver image, the network could recognize important features in DBT images, distinguishing them from image noise. The resulting image visually preserved the important structures of the image and greatly reduced the noise. There appeared to be some artifacts, but they looked minor. More rigorous evaluation needs to be performed, but the technique looks, if not promising, at least interesting.

Another interesting application of deep learning was from a group at the University of California, San Francisco, and presented by Hari Trivedi, MD. They reported on training a deep learning model to detect breast cancer on screening and diagnostic mammograms. One of the difficulties when using deep learning is that large volumes of data are needed for training, and collecting, storing and transferring them can be difficult. The novel application of deep learning in this case was to search through the DICOM headers of a large number of cases to find appropriate ones for training. That was not the main thrust of their paper, but it was interesting and could accelerate future deep learning applications.

Two other physics talks on DBT, not involving deep learning, were noteworthy. The first was presented by Aldo Badano, PhD, from the Food and Drug Administration (FDA), and was entitled "Digital Breast Tomosynthesis as a Replacement of Full-Field Digital Mammography for the Detection of Breast Cancer: An Open-Source, In-Silico Clinical Trial." This presentation was the product of many years

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of research from his colleagues at the FDA to develop a virtual clinical trial—that is, a large-scale simulation of digital mammography and DBT using multiple models for the breast, breast lesions, imaging physics, and radiologist readings. They compared their simulation performance to published clinical trials. They showed that for digital mammography the in silico performance was comparable to published trials with actual patients and radiologists. The ultimate goal of this research is to be able to simulate clinical trials with many different imaging conditions and scenarios that would otherwise be impractical with actual patients.

The second DBT talk was presented by Hailiang Huang, MS, who is a graduate student of Wei Zhao, PhD, from the State University of New York at Stony Brook. It was entitled "Comparison of Contrast-Enhanced Dual Energy Mammography (CEDEM) and Contrast-Enhanced Digital Breast Tomosynthesis (CEDBT) for Lesion Assessment and Radiation Dose." They used a Siemens MAMMOMAT Inspiration tomosynthesis system to image 12 patients, all of whom had either a BI-RADS 4 or 5 lesion and were scheduled for a biopsy. They performed a side-by-side comparison and found that CEDBT provided better lesion margin identification and reduced structural noise due to background parenchymal enhancement and motion compared with CEDEM, but the intensity of lesion enhancement was lower. The difference could be due in part to the wider angular sampling of the Siemens system compared with other DBT systems.

Finally, I would like to comment on a talk from a breast session. It was entitled "Detecting Breast Cancer in Mammography: How Close Are Computers to Radiologists?" Now of course we all know what the answer is going to be: they are comparable. This talk was from the physics group in Nijmegen University and was led by Ioannis Sechopoulos, PhD. They obtained images from previously performed observer studies and ran them through a commercial computer-aided detection (CADe) system. They then compared the performance of the CADe system, which is a sensitivity and specificity point, with the performance of the radiologists who participated in the observer studies, which were displayed as curves. The points (CADe system) generally fell within the spread of the different curves (1 for each radiologist). Before you worry about your job, there is one large caveat that the presenter did not mention. Several years ago, David Gur and his colleagues from the University of Pittsburgh demonstrated what is known as the "laboratory effect": radiologists perform differently in observer studies than in a true clinical setting. In fact, radiologists generally perform slightly better clinically than they do in observer studies. So the conclusion from the talk is that computers are as good as radiologists in observer studies. It remains to be seen if computers are as good as radiologists in true clinical practice, although in my opinion computers will soon be as good as the average radiologist reading screening mammograms in clinical practice. ❖