Deep Learning-enabled Ultrasound Imaging – Opportunities, Risks, and Challenges

Benny Lam
Philips Ultrasound
February 2020

Acknowledgements

- Charles Tremblay-Darveau
- David Hope-Simpson
- Dave Shoultz
- Deep Pal
- Hans-Aloys Wischmann
- Homer Pien
- Robert Trahms
- T.J. Battisti
- Thanasis Loupas
- Pat Baird
- Patrick Jones

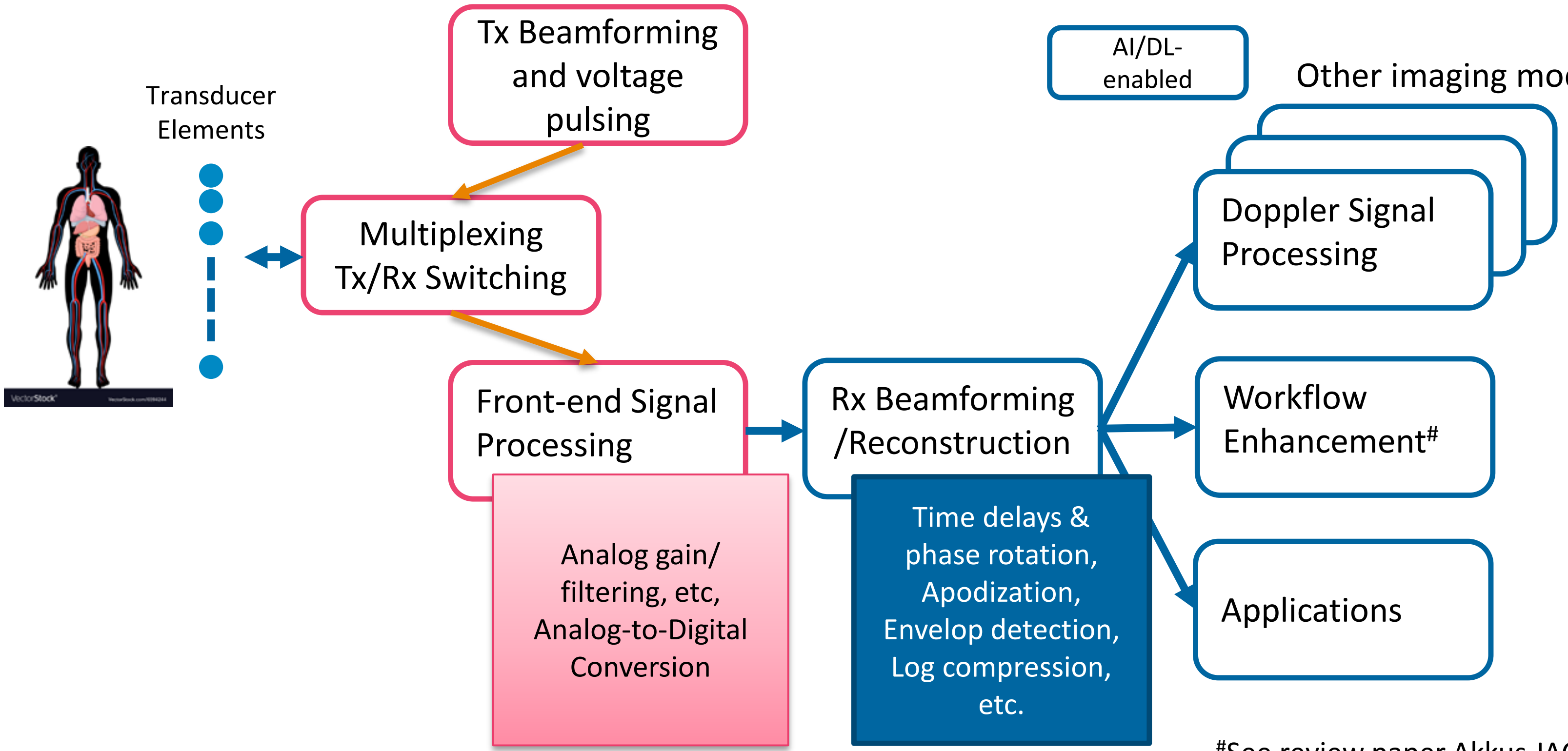
What ultrasound currently can offer and clinical users' demands

- Ultrasound imaging offers
  - Portable
  - Real-time and Interactive
  - Point-of-care diagnosis
  - Multi-functional
  - Cost-effective
  - No ionizing radiation

- Top clinical user demands (from Society of Radiologists in Ultrasound 2019)
  - Image quality (top priority)
  - Workflow
  - Applications (e.g. quantification, disease classification)

- How AI can satisfy some of these demands from image acquisition's perspective?

How Artificial Intelligence/Deep Learning has been used in ultrasound imaging?



#See review paper Akkus JACR2019
Tx: Transmit
Rx: Receive

Benefits of Using DL in Ultrasound Imaging

<table>
<tr><td rowspan="5">Engineering</td><td>Offer higher flexibility in development
DL model can be used to develop one component of the imaging chain or end-to-end chain
DL model can operate on RF data, beamformed data, reconstructed images</td><td rowspan="5">More flexible, robust, and generalizable than classical image/signal processing methods</td></tr>
<tr><td>More computationally efficient and robust
Adaptive
Bypass complex mathematical model through learning by examples
Minimal manual parameter tuning
Intrinsically exploit hidden relationships in data</td></tr>
<tr><td>Replicate complex algorithm calculations in much shorter time</td></tr>
<tr><td>Minimal to none handcrafted feature extraction</td></tr>
<tr><td>Development can become more data efficient by leveraging existing knowledge on imaging physics and engineering (human intelligence)</td></tr>
<tr><td>Clinical</td><td>Faster and easier image acquisition without sacrificing image quality
Emulate complex/expensive hardware with simpler/cheaper hardware
More streamlined workflow
More sophisticated applications</td><td>Better user experience for clinicians and quality of care for patients</td></tr>
</table>

Technological Challenges

	Technological challenges addressed/covered by existing regulatory frameworks:	Technological challenges that might require consideration with existing frameworks:
Data quality and governance	• Validation dataset provenance, quality, and match to intended use	• Training dataset provenance, quality, and match to intended use
Image quality evaluation	• In validation and during ongoing clinical use	• Adequacy of existing image quality evaluation method • Frequency of image quality check after release • Change in risk level w.r.t. intended use
Bias detection and correction	• Check validation datasets and results for potential bias	• Check training datasets and intermediate results for potential bias • Extrapolation of trained neural net to new data • Apply Good Machine Learning Practice

Regulatory Challenges

- Accelerated release of “retrained and refrozen” improvements within original intended use
- Regulatory submission preparation and review vs product development timeline
- Regulatory science development to align with the speed of technology advancement
- Balance between transparency and information overload

Outlook and Opportunities – for AI/DL-enabled radiological imaging devices

- Leverage and re-calibrate existing FDA's regulatory approaches and tools
  - Tools have already developed have set up a good foundation
  - How to make the best out of them?

- Agile quality evaluation and monitoring system
  - Combination of performance measures, monitoring, feedback, and mitigation mechanisms
  - Benefit-risk assessment framework adaptive to range of benefit and risk levels
  - Flexibility in Pre- and Post-market data to demonstrate TPLC safety and effectiveness
  - Real world performance

- Practice guide for data governance
  - Build trust on the data we used (and are going to use) in training and testing (representative, avoid bias, reflect clinical outcome)

- User education
  - User training, risk and benefit awareness, channels for reporting issues

- We share the responsibility to ensure patients' safety and well-being

PHILIPS

Beamforming/Reconstruction

Purposes	Transform received ultrasound signals to **images** for diagnosis or for further processing		
Conventional methods and shortcomings	• Delay-and-Sum Beamforming - Low computational complexity and fast, but limited image quality • Minimum Variance (MV) Beamforming - Adaptive, but extremely **computational complex**, limit the application for real world (e.g. **long reconstruction time** for matrix-transducers) • Require full-sampling -> **long acquisition time**		
How DL was used	**Estimate sub-sampled RF data** by **exploiting RF data redundancy** in Rx-Tx and Rx-Scan Line domains through low rank Hankel matrix decomposition -> fast imaging	**Increase reconstruction speed** by 400 times by replacing the bottleneck **(apodization weights calculation)** in MV beamformer through **mapping the weights for each pixel**	Perform **fast end-to-end reconstruction at MV beamformer quality** with a medical ultrasound-specific loss function[1] through mapping time-delayed raw data to a minimum variance ground truth
Training Input/target Data	Sub-sampled multi-line acquisition (MLA) data/original B-mode MLA data	Pre-delayed array response for a particular pixel/ corresponding array apodizations	Time-delayed channel data/ MV-beamformed data
References	Yoon IEEE TMI 2019	Luijten ICASSP 2019	Simson IEEE IUS 2018
DL offer	Improve beamforming/reconstruction **speed** and **flexibility** for better **clinical workflow** and **expanded applications** without sacrificing clinical **image quality**		

[1] peak signal-to-noise-ratio (PSNR) loss, and the multi-scale structural similarity index (MS-SSIM) loss via a weighting factor

Doppler Signal Processing

Purposes	**Spectral Doppler** **Estimation of blood and tissue velocity** distributions from slow-time data sequences, i.e. a series of subsequent pulse-echo snapshots	**Tissue Doppler Echography Encoding** **Measure myocardial strain rate and tissue velocities** for detecting epicardium-parietal pericardium border and quantification of stiffening of developing lesions
Conventional methods and shortcomings	• Fourier-transform-based periodogram methods – fast but **time-frequency resolution tradeoff** • Adaptive spectral estimators – better spectral estimate and resolution but **computational complexity is high**	• Phase estimate from pulse-to-pulse autocorrelation – **noisy, limited accuracy, time-spatial resolution tradeoff**
How DL was used	**Solving for filter bank coefficients** in adaptive spectral estimators to obtain spectral estimates	**Learn Doppler measurements** based on an encoder-decoder architecture w.r.t. Kasai autocorrelator
Training Input/ Target Data	Beamformed slow-time RF/ filter coefficients for each filter in the filter bank	IQ data ensemble/Kasai Doppler estimates (axial velocity)
References	van Sloun Proc IEEE 2019	van Sloun IEEE IUS 2018
DL offer	Provide **computational efficient method** while maintaining spectral estimate accuracy and resolution	**Learn algorithm by example**

Applications: Contrast-enhanced Imaging

Purposes	**Contrast-enhanced Ultrasound (CEUS)** **Image blood volume and flow** at capillary level and provide quantitative information	**Super-resolution Imaging/ Ultrasound Localization Microscopy** **Image deep vasculature** at very high (mm) resolution
Conventional methods and shortcomings	• Second harmonic imaging to separate non-linear response of microbubbles from tissue's – but **tissue also exhibits nonlinear response** • Spatio-temporal filtering (**SVD**) – **threshold** settings for tissue and blood signals **depend on scans and subjects** & require **many iterations** to converge	• Identify centroid of **PSF from sparse microbubbles** and project over time – but sparse bubble paradigm **significantly increases scan times** (practically non-viable) • **High-density microbubble paradigm** leads to **blurry image** due to extensive microbubble PSF overlap
How DL was used	**Solve the convolution in PCA** for the decomposition problem for tissue & blood signals through backpropagation	Locate PSF centroid based on **simulation** of an encoder-decoder architecture
Training Input/ Target Data	Beamformed images/Simulated and in-vivo decomposition of tissue and blood signals	Synthetic down-sampled RF CEUS signals/ super-resolved microbubble locations with varying density, intensity
References	Li ICASSP 2019, vanSloun ProcIEEE 2019	vanSloun ICASSP 2019, Errico Nature 2015
DL offer	**Remove clutter signals** from stationary or slowly moving tissues in a computationally efficient, robust, and adaptive way	Obtain **super-resolution** image in near real time from high-density microbubble paradigm