

End-to-end deep learning for tuning-free non-contrast ultrasound microvessel imaging

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INTRODUCTION

- Microvascular imaging with US without a contrast agent is difficult due to the presence of tissue clutter.
- Singular value decomposition (SVD) has been used to remove tissue clutter echo from blood flow signals [1,2].
- Challenges:**

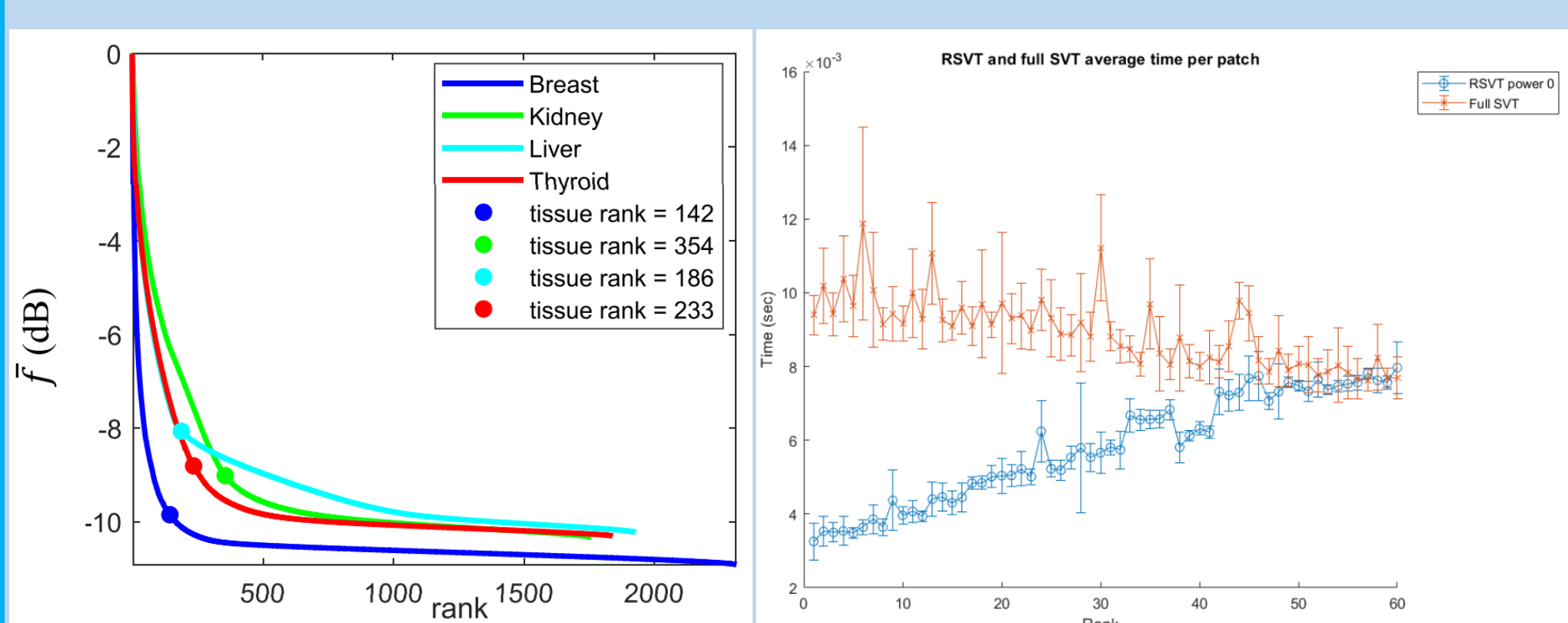


Figure 1: SV decay profiles show different rank choices for different tissue clutter removal [5].
Figure 2: SVD and accelerated rSVD are computationally expensive [1].

- Deep learning (DL) based vascular imaging approach can
 - approximate or extend SVT, e.g., for variable ensemble lengths, without explicit fine tuning
 - reduce computational cost during test time, making vascular imaging possible with a fast acquisition, especially on resource-constrained portable devices.
 - Extend utility across platforms via transfer learning and augmentation
 - Adapt to tissue+blood behavior, variable SNR, etc. via additional learning and augmentation.
- We proposed an end-to-end deep convolutional neural network-based approach for removing tissue clutter from US data to image microvessel (MV).

IMAGING EXPERIMENT

- We scanned a day 8 chicken embryo using a Vevo 3100 (VisualSonics Inc.) system and an MX250 transducer (center transmit frequency: 21 MHz).
 - Focal depth: 7 mm into the embryo.

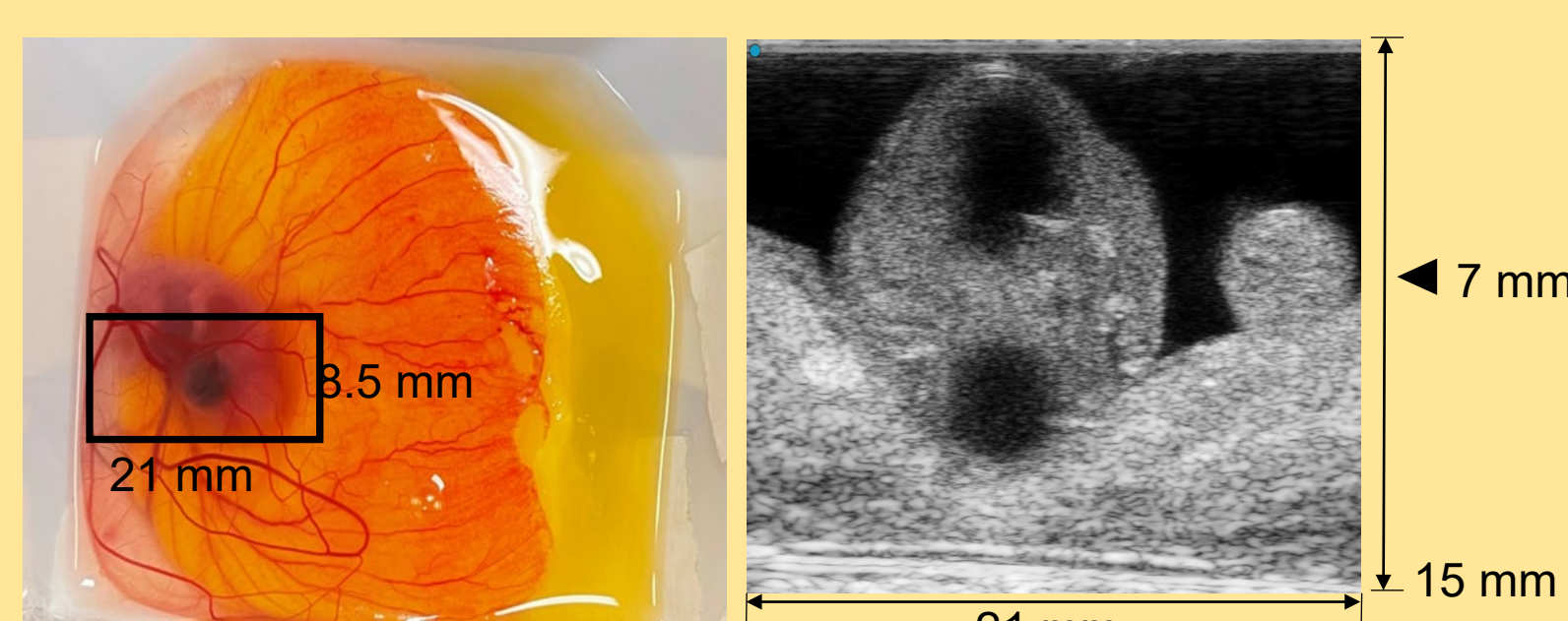


Figure 3. Left: 3D-UBM system, Center: 8-day old chicken embryo. Right: Sample image of the embryo in the brain region.

- Embryos were grown according to Meijlink et al.[3]
 - Embryos were stored at 37°C and 50-60% humidity for 8 days in an incubator with automatic egg turning.
- On day 8, embryos were carefully extracted from the shell and placed in a weigh boat that was kept at 37°C until imaging began.
- The embryo chorioallantoic membrane (CAM) surface was directly coupled with the ultrasound transducer using ultrasound gel.
- 3D imaging data was acquired by modifying previously developed 3D-UBM system [4] with a step size of 50µm.
- The experiment took approximately 3 hours and the embryo's heart continued beating for the duration.

METHODS

Spatiotemporal data processing

- Spatiotemporal IQ data $s(x,y,t)$ was processed via SVT reported before [2], [5].
- Spatiotemporal data s contains IQ data containing amplitude and phase of the US echo which are both used for removing tissue clutter.
 - Blood consists of flowing heterogeneous scattering elements (e.g., blood cells, platelets, etc.) in a fluid. This produces a complicated, high-rank spatiotemporal echo matrix.
- We computed a low-rank approximation of the complex IQ data and removed the first $k = 30$ singular vectors spanning the signal to remove tissue clutter.

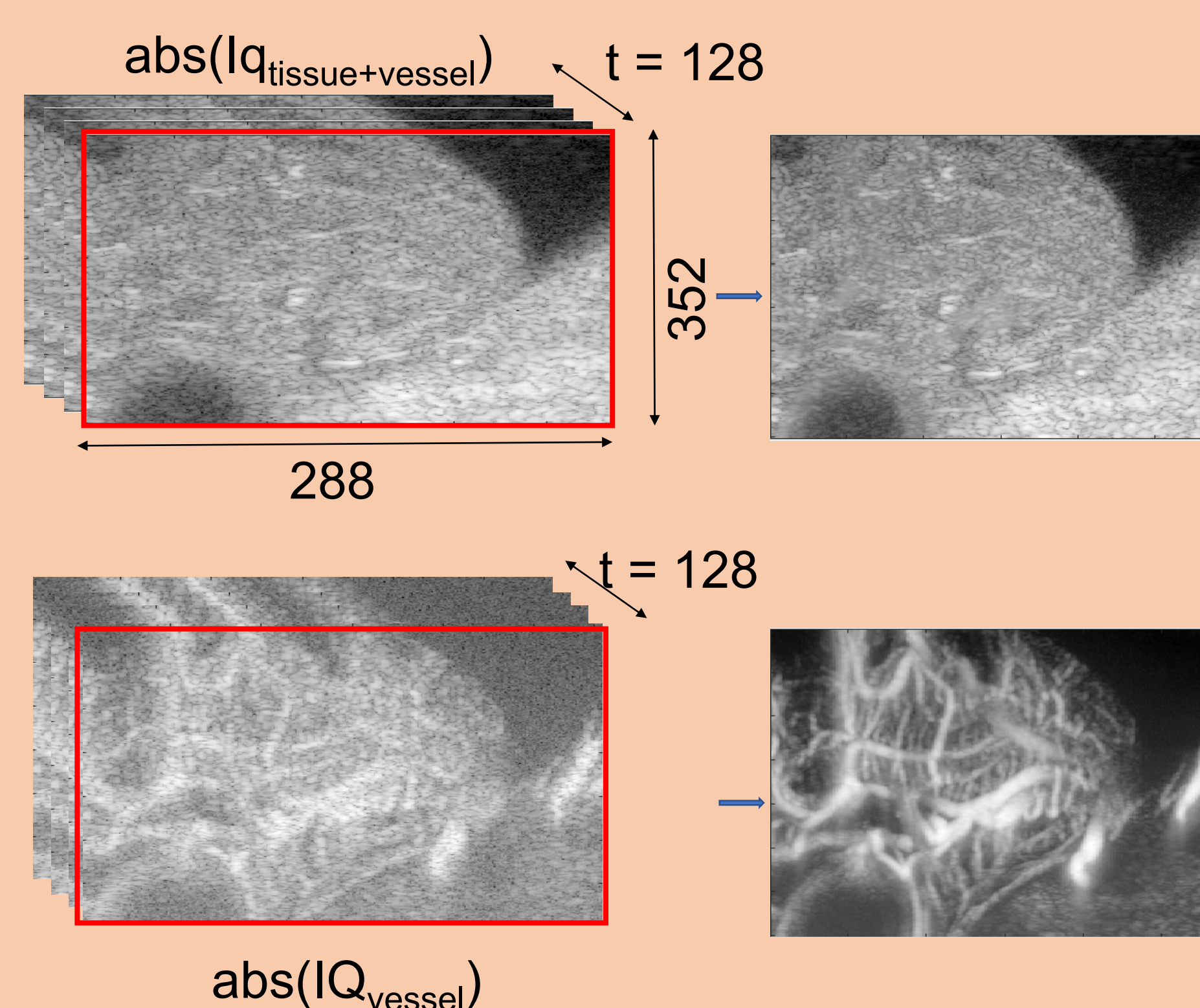


Figure 4. Magnitude of the complex IQ data, $|s|$ before (top) and after (bottom) SVT. Top-left and bottom-left show the US ensemble. Top-right and bottom right show log-normalized intensity projection of the ensemble.

Deep neural network training

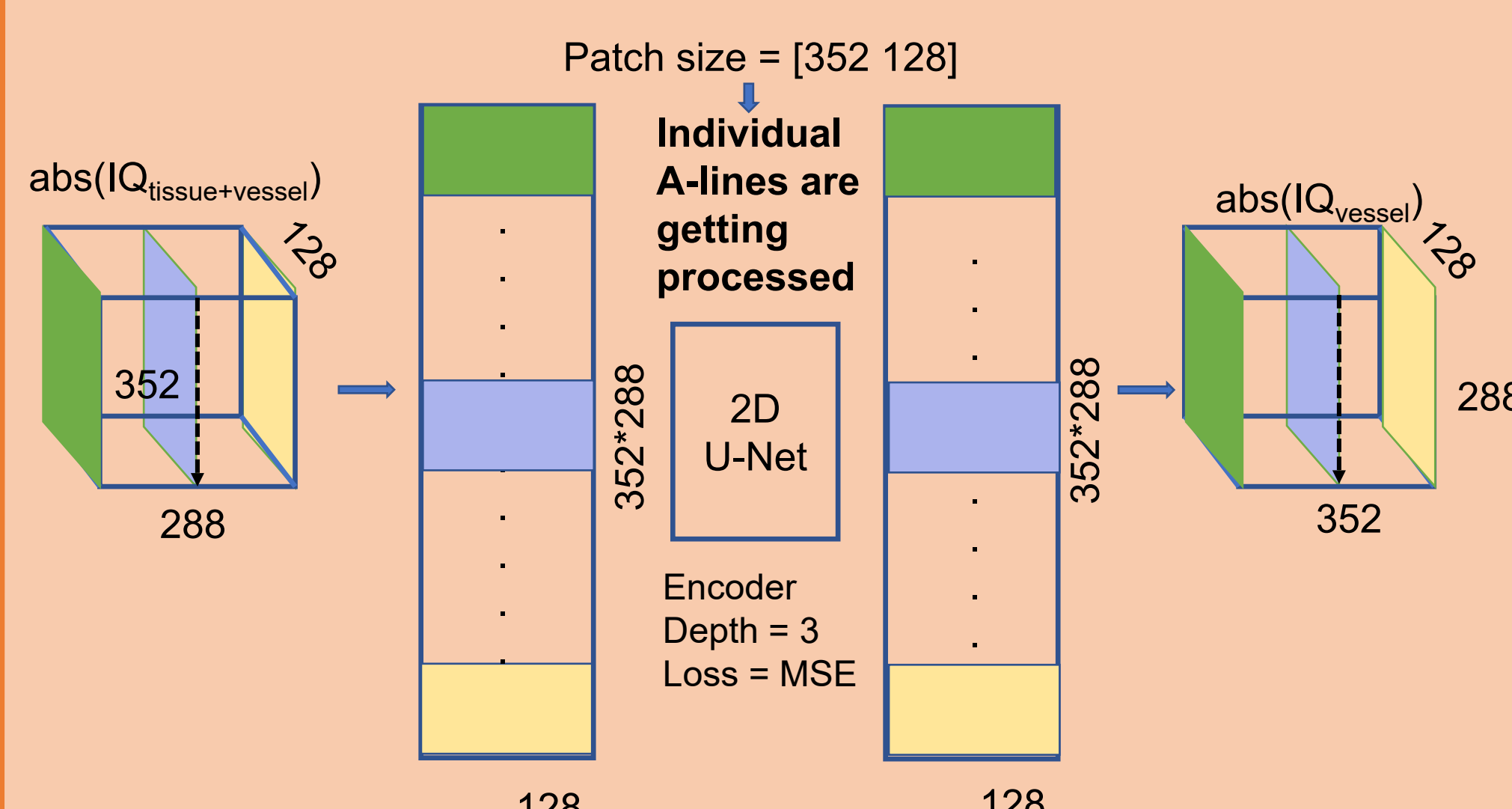


Figure 5. Proposed end-to-end DL approach to extract MV from US ensemble. A 2D U-net was used to train the input patches. During testing, patches were evaluated and stitched together to create the MV image.

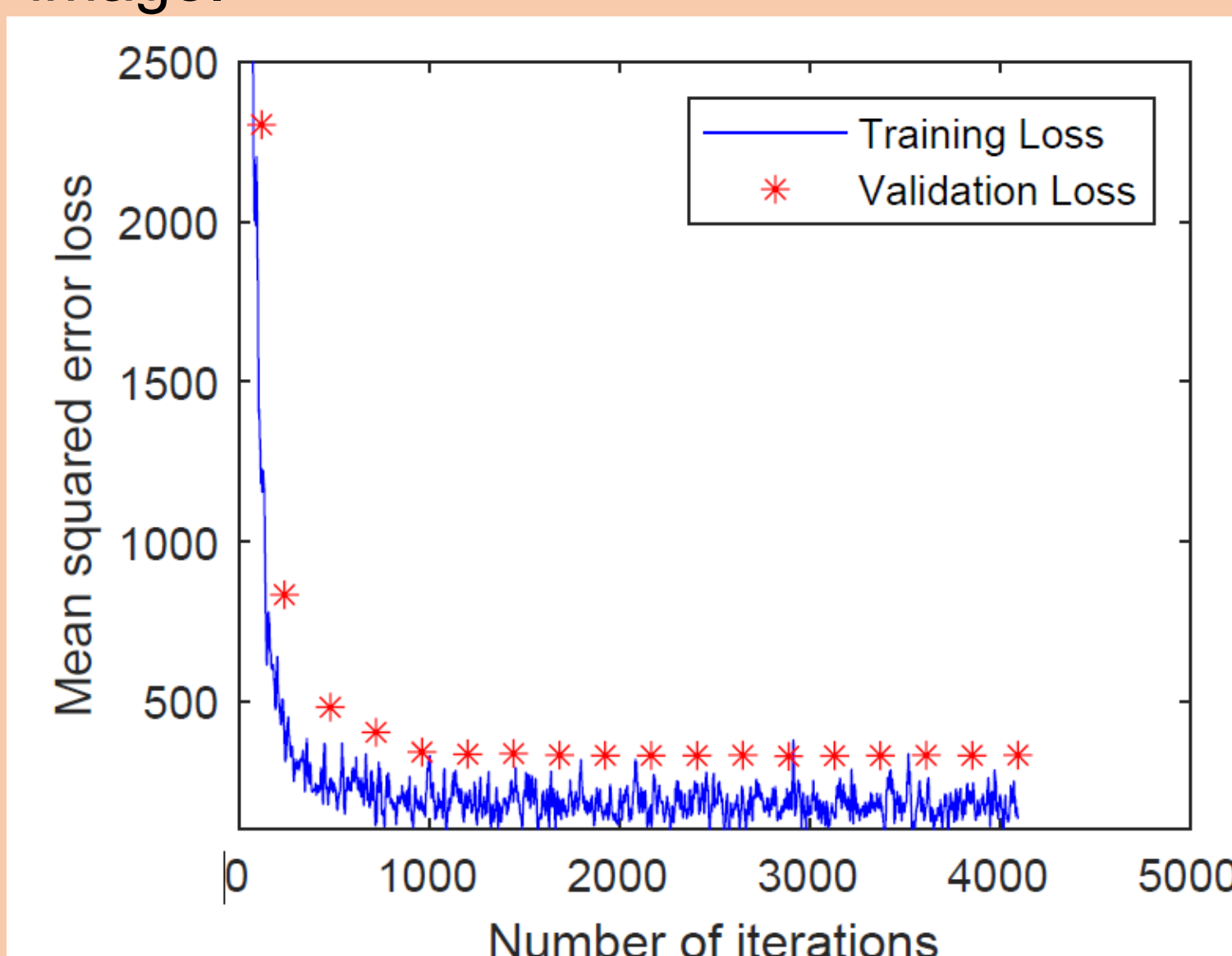
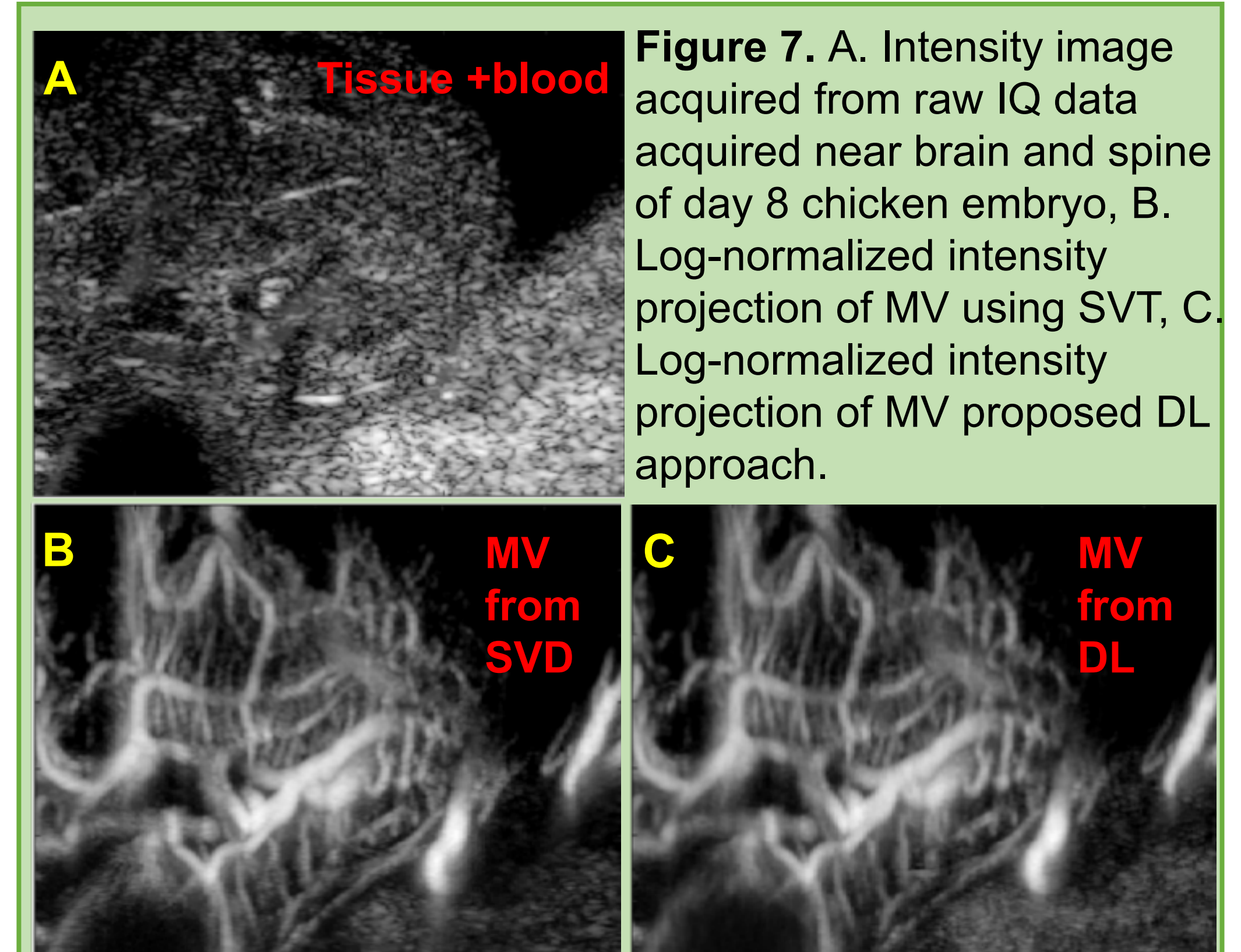


Figure 6. Training and validation loss. Early stopping was used when validation loss did not improve.

DATASETS

- We collected spatiotemporal IQ data from 114 locations along the embryo.
- First 128 frames were chosen for further processing, leading to IQ data of 352x288x128 for our deep learning approach.
- Data from three separate regions of the embryo were divided into training (69 from heart), validation (29 from heart), and testing (16 from brain) to ensure no overlap.

RESULTS



- SSIM = 0.83 ± 0.02 in log-normalized vascular images between SVT images and DL predictions, implying good reconstruction.
- While SVT works on both amplitude and phase data, proposed deep learning predictions are from amplitude of IQ data alone so it can be applied to any imaging system without requiring raw data.
- DL based approach was also 2x faster.

DISCUSSION

- Our proposed deep neural network can successfully remove tissue clutter from US ensemble and makes the process faster than traditional SVT approach.
- While SVT relies on complex IQ data and careful selection of rank, DL can be extended to adapt to amplitude data only and different scenarios to admit realistic tissue motions and under noisy conditions.

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