Individualized Spinal Cord Injury Treatment Using AI-Guided Focused Ultrasound: Optimization of Implantable Device Placement with Physics-informed Operator Learning

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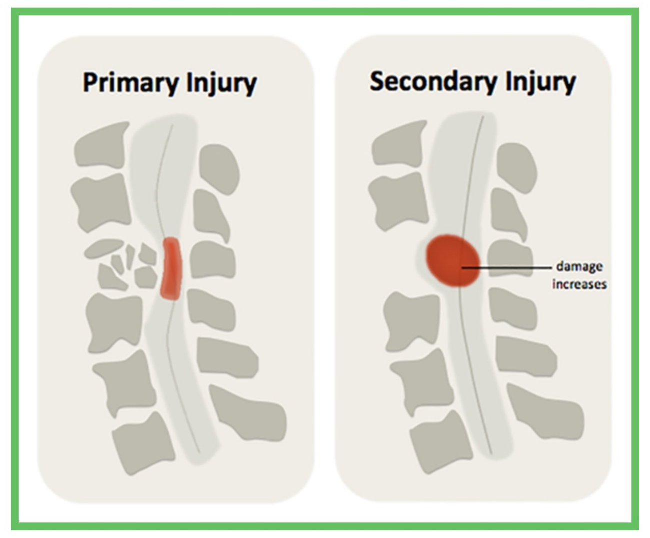
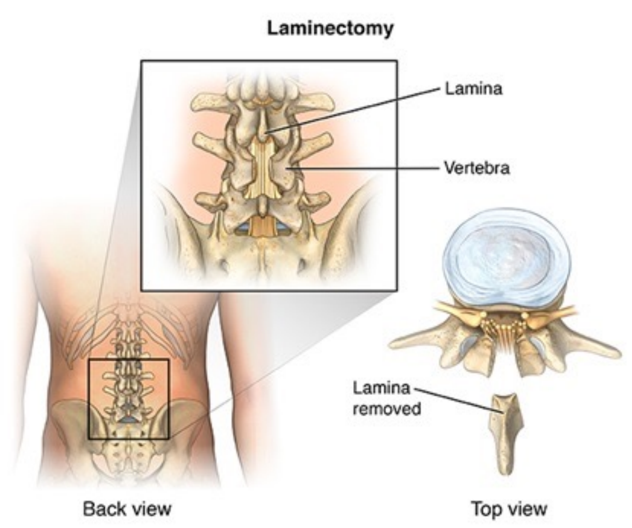
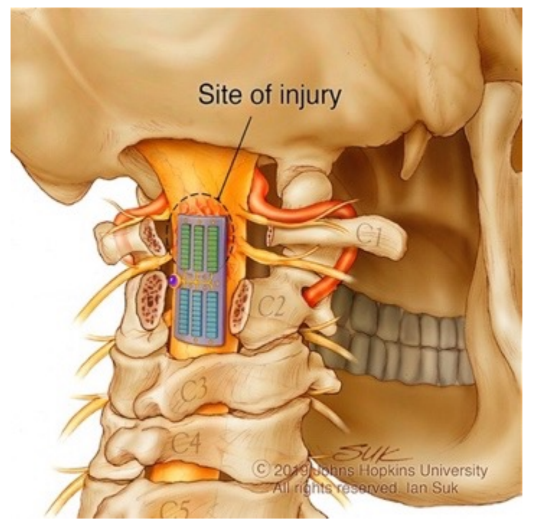
The Promise of FUS

Spinal cord injury (SCI) impacts 282,000 people a year in the United States [1].



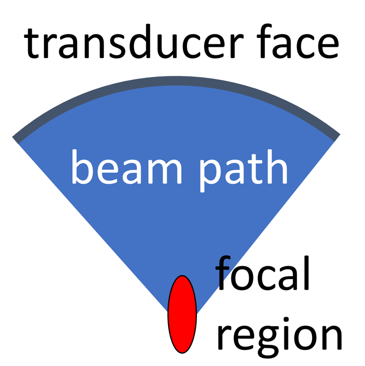


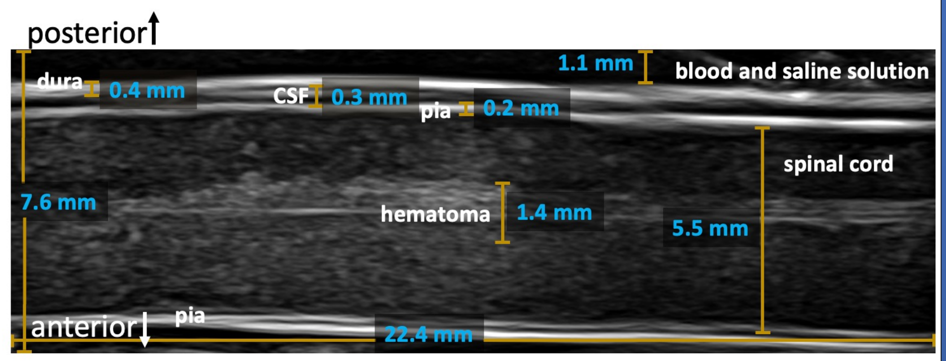
Focused ultrasound (FUS) can promote healing in a controlled manner [2, 3]. The effectiveness of therapeutic ultrasound is determined by probe location. ***We want to minimize exposure of the focused beam on healthy tissue while simultaneously targeting the injury site.***



MUSIC: The implantable ultrasound device with both imaging (green) and focused ultrasound (blue) to monitor and treat patients with spinal cord injury.

Considerations





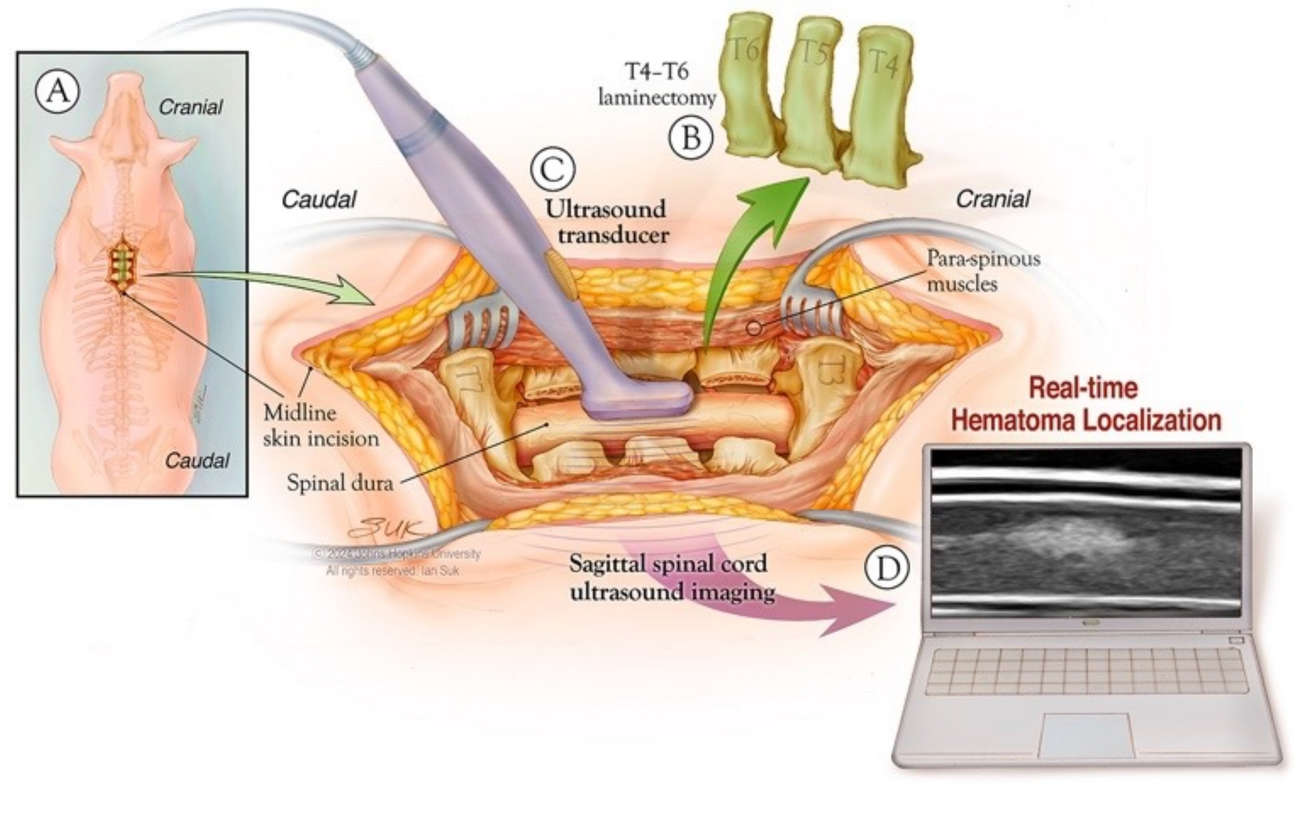
<u>Defocusing of the beam due to distortion as it propagates through the tissue can lead to ineffective therapy or additional tissue damage and paralysis.</u>

To accurately predict where the FUS beams will focus within patient-specific spinal cords, we must use computer simulations which numerically solve the governing equations of ultrasound wave propagation in heterogeneous media.

Data Processing

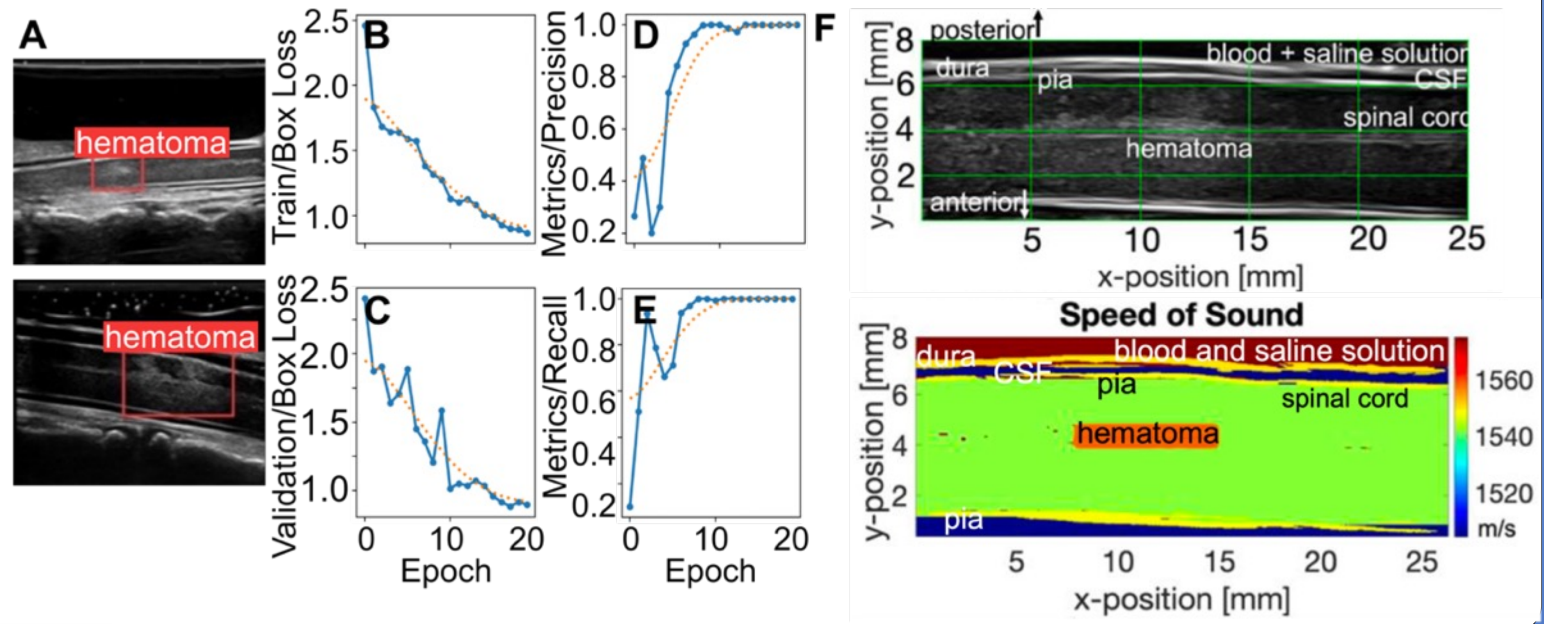
Image Acquisition:

- Laminectomy performed from the 4th to 6th thoracic vertebra to provide an acoustic window in a female pig
- 23-gram weight drop in the 5th thoracic level (T5) of the cord
- B-mode images of the sagittal cross section collected with Canon Aplio i800 ultrasound system connected to an i22LH8 transducer



Preprocessing steps:

- Automatic hematoma localization and semantic segmentation of spinal cord for injury monitoring.
- Segmented images of the injured spinal cord → computation grid in k-Wave.



Preliminary Simulations

k-Wave: computationally equivalent to a generalized Westervelt equation, this simulation toolbox approximates acoustic wave fields on a specified computational grid using these PDEs,

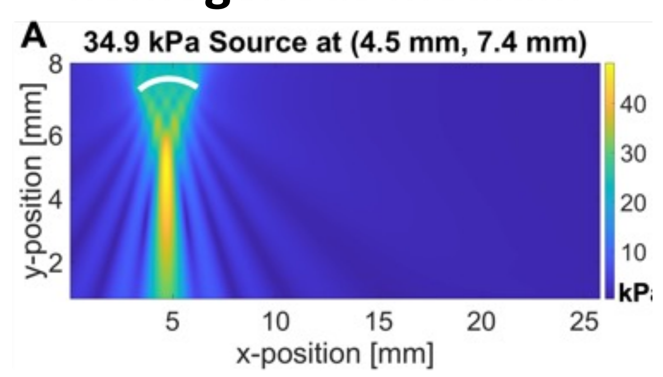
$$\frac{\partial \boldsymbol{u}}{\partial t} = -\frac{1}{\rho_0}\nabla p + S_F \quad (1)$$

$$\frac{\partial \rho}{\partial t} = -\rho_0 \nabla \cdot \boldsymbol{u} + S_M \quad (2)$$

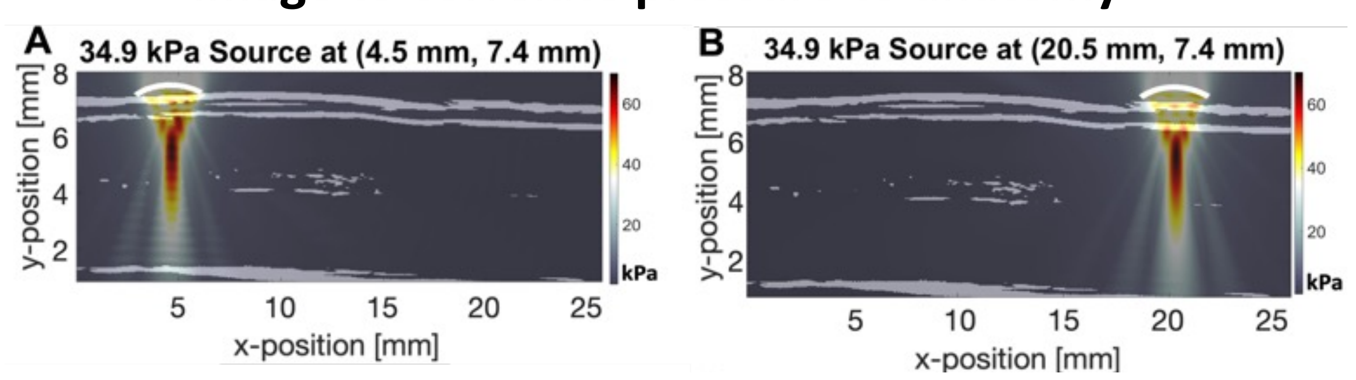
$$p = c^2 \rho \quad (3)$$

where $\boldsymbol{u}$ is the particle velocity, p is the acoustic pressure, ρ is the acoustic density, *c* is speed of sound, ρ_0 is the equilibrium density and S_F, S_M are the force and mass source terms [4].

Maximum pressure (kPa) in a homogenous medium



Maximum pressure (kPa) overlaid on the ultrasound image to correlate pressure to anatomy



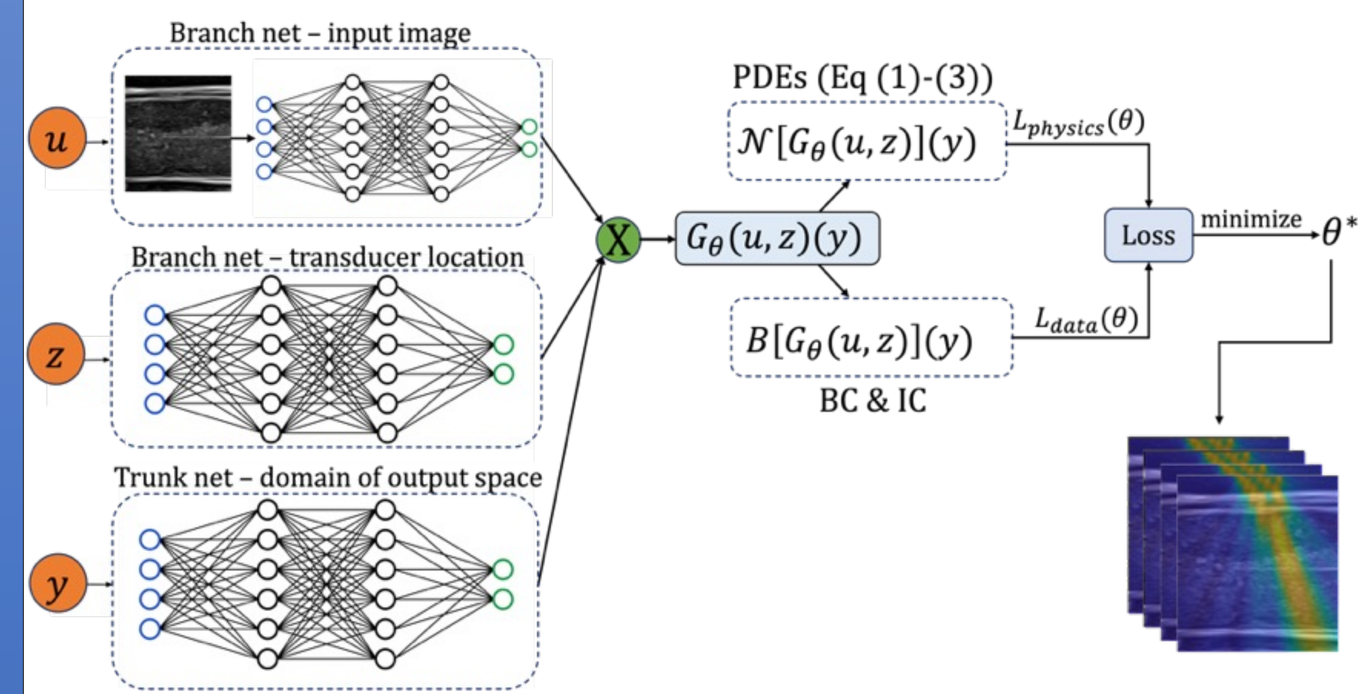
Traditional numerical methods come with a bottleneck: for each new input (i.e., transducer location, patient anatomy), the model needs to recompute the solution (pressure distribution), a computational luxury that cannot be afforded in a time-sensitive environment like the operating room [5].

Proposed Approach

Physics-informed DeepONet for real-time automatic generation of pressure distribution fields in patient-specific spinal cords [6, 7]

- Learn the mappings between the **changing parameters** (transducer location, patient-specific anatomy) **and the governing PDE solution** (pressure distribution)
- Trained on the high-fidelity simulated pressure maps

Optimizing FUS placement: with real-time pressure map solutions, clinicians can identify optimal transducer placements in a matter of seconds— a stark contrast to the 30-minute simulation run-time per location (up to 150 minutes for 5 locations on a given patient image).



<u>Expected outcomes:</u> We anticipate that our network will compute high-accuracy pressure fields up to **1000 times faster** than traditional simulations, demonstrating the practical applicability of operator learning in surgical medicine, particularly for optimizing the use of neural implants.

Future directions: Expand to human pipeline [8].

References

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