Deep Learning-based Needle Detection in Ultrasound[1]

1. General Info

Project Title: Deep Learning-based Needle Detection in Ultrasound
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2. Project Abstract

Imagine being at the forefront of medical practice—your work helping doctors accurately guide needles even when they're nearly invisible in ultrasound (US) images! This project endeavor to tackle the challenge of detecting a needle in ultrasound-guided intervention procedure, even when the needle becomes hard to see. By gently vibrating the needle at a specific frequency, we can capture a series of dynamic ultrasound images that reveal the needle's position in a way that under explored. These images will feed into a powerful neural network designed to precisely detect the needle tip and calculate the insertion angle. *We have already collected a number of US video clips for training.* Therefore, the main tasks of this project will be *i).* constructing a dataset from the raw data, and *ii).* reproducing, as well as *iii).* potentially modifying a model that we designed in our previous work[1] or other SOTA models.

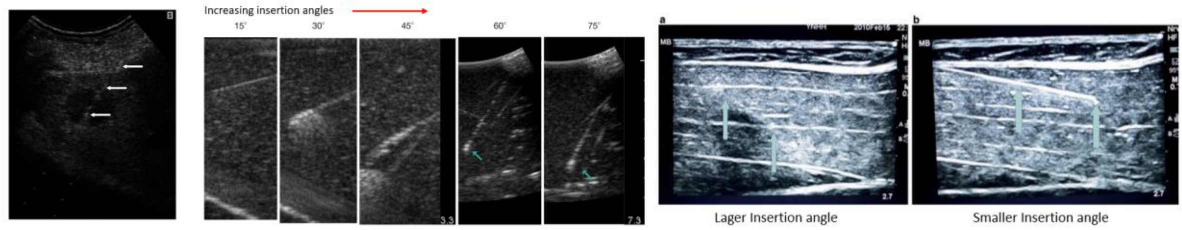

Figure 1 An illustration of the reduced visibility of the needle with increasing insertion angle for *Left:* the ultrasound-guided biopsy of a hypoechoic liver lesion, due to the *Right:* the scattering of the ultrasound wave

3. Background and Motivation

Ultrasound-guided intervention percutaneous needle insertion is ubiquitously used in clinical practices[2], such as drug delivery, regional anesthesia, tissue biopsy, etc. Compared with CT, MRI and other imaging modalities, ultrasound (US) distinguishes itself by offering the advantages of being radiation-free and real-time imaging. However, challenges remain when performing needle insertion due to its inherent low resolution, the existence of speckle noise, and the minor misalignment between the imaging and target planes, which makes it difficult to discern the inserted needle from the surrounding tissue in US images[3, 4]. A robust needle-segmentation

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[2] Y. Kuang, A. Hilgers, M. Sadiq, S. Cochran, G. Corner, and Z. Huang, "Modelling and characterisation of a ultrasound-actuated needle for improved visibility in ultrasound-guided regional anaesthesia and tissue biopsy," Ultrasonics, vol. 69, pp. 38–46, 2016.
[3] G. Reusz, P. Sarkany, J. Gal, and A. Csomos, "Needle-related ultrasound artifacts and their importance in anaesthetic practice," British journal of anaesthesia, vol. 112, no. 5, pp. 794–802, 2014..
[4] Z. Jiang, S. E. Salcudean, and N. Navab, "Robotic ultrasound imaging: State-of-the-art and future perspectives," Medical image analysis, p. 102878, 2023
[5] D. J. Gillies, J. R. Rodgers, I. Gyacskov, P. Roy, N. Kakani, D. W. Cool, and A. Fenster, "Deep learning segmentation of general interventional tools in two-dimensional ultrasound images," Medical Physics, vol. 47, no. 10, pp. 4956–4970, 2020
[6] Aksan E, Kaufmann M, Cao P, et al. A spatio-temporal transformer for 3d human motion prediction[C]//2021 International Conference on 3D Vision (3DV). IEEE, 2021: 565-574.
[7] Park J, Kim H S, Ko K, et al. VideoMamba: Spatio-Temporal Selective State Space Model[J]. arXiv preprint arXiv:2407.08476, 2024.

algorithm will not only increase the success rate of the medical procedures but also enhance efficiency while minimizing the risk of damage to critical organs.
Despite the significant advances in deep learning methods (e.g. UNet[5]), the performance of the needle tracking networks decreases when the needle's visibility is reduced. To address this challenge, we developed a mechanism to vibrate the inserted needle and collect a large amount of data. This data is then used to train a deep learning model that accepts spatiotemporal (ST) data (i.e., sequential US images) as input and outputs the needle tip location and insertion angle. By vibrating the needle, we can extract more information from the images, thus improving the needle detection performance.

4. Technical Prerequisites

- Good background in training deep neural networks
- Good skills in Python, OpenCV
- Good skills in PyTorch

5. Benefits:

- Possible novelty of the research
- Possible publication

6. Students' Tasks Description

Students' tasks would be the following:

1. *Literature review:* Gaining an understanding of the project's goal, identifying factors that reduce needle visibility, and what are the potential ways to address this challenge.
2. *Dataset construction:* constructing a dataset from raw data deepens understanding of network design and highlights considerations for the training process.
3. *Implement UNet/WNet as toy example:* Establishing a baseline sets a reference point to evaluate the performance of the proposed methods.
4. *Reproducing and modifying SOTA models*: understanding how to manipulate the spatiotemporal data given the goal of this project. Understanding how spatiotemporal data is processed in relation to the project's goal. Along with the references we provide, we can discuss plausible ways to improve the current network structure. The SOTA models would involve VibNet[1], Transformer[6], Mamba[7], etc..

7. Work-packages and Time-plan:

	Description	Time Period
WP1	Familiar with the literature.	2 weeks
WP2	Construct a dataset from the raw data	1 week
WP3	Implement UNet/WNet as toy example	2 weeks
M1	**Intermediate Presentation II**	
WP5	Choosing, Reproducing and evaluating a SOTA model	4 weeks
WP6	Modify the structure of the chosen model	2 weeks
WP8	Testing and Documentation	1 week
M2	**Final Presentation**	