Project Progress Report - Ultrasound Imaging Optimization via Machine Learning

Group Number: 80

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1. Background

Ultrasound (US) imaging is a safe and powerful tool for providing detailed still and moving images of the human body. Due to the Delay And Sum (DAS) imaging algorithm, images reconstructed from the soft probe integrated into human skin will be significantly distorted by the position noise. We expect our project to fix the distorted images. Moveover, we want our model to autonomously classify ultrasound images for any person without guidance from trained personnel.

2. Dataset name

Ultrasound B-mode Imaging of Carotid Artery Dataset. (organized by ourself)

3. Dataset citation/link

The dataset is established via two steps: First, a commercial US simulation system called Verasonics is applied to generate the US signal with different shapes of US probes. Second, the US signal is processed by a DAS module to form the US images with/without position errors. The DAS module is developed by python and a wearable ultrasound research group at UCSD (Prof.Sheng Xu's group: http://xugroup.eng.ucsd.edu/) provides guidance for this part.

The dataset link is at: https://github.com/tony1945/ECE228ProjectProgressGroup80

4. Is feature extraction used

Answer using Yes/No, if you are doing feature engineering for one/more of your planned models

NO

5. If you answered yes to 4, what features are you planning to extract (with citations on where these are used)

Fill in the answers to the following

- 1. Features used in literature (if any?) that you are using here:-
- 2. Other features which you are confident about using:-
- 3. Features that you want to try which haven't been explored in literature:-
- 6. What model(s) are used:-

Simply name the model(s) you are using in order of highest to lowest priority for implementation

1. Model Architecture from literature that you plan to use:

YOLO v3 & Autoencoder

2. New architecture experiments you want to try:-

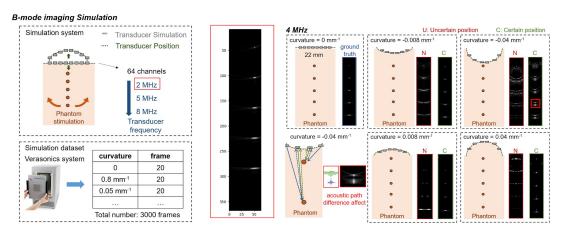
7. Progress Report

Details on your progress. Effort taken on dataset collection, feature extraction, what tests you have run etc.

1. Build a dataset with position noise for quick dirty try

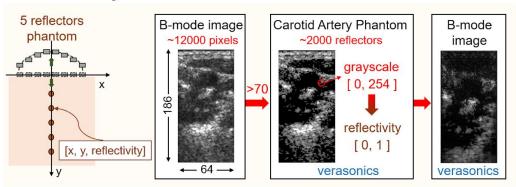
Currently, we have already finished our simulation system and collected around 3000 ultrasound images of human carotid arteries. These ultrasound images can be divided into two groups: one group is the images formed by DAS with correct transducer positions, this group is the ground truth during the training process; another group is the images formed by DAS with wrong transducer positions, the position errors or noises include: convex or concave shapes with random curvature and sinusoidal shapes with random parameters.

In order to quick-try our entire workflow, the simulation process first started with some sample reflectors:



Then we build a serial of carotid artery phantoms base on the real medical B-mode images and collect more data from new phantoms:

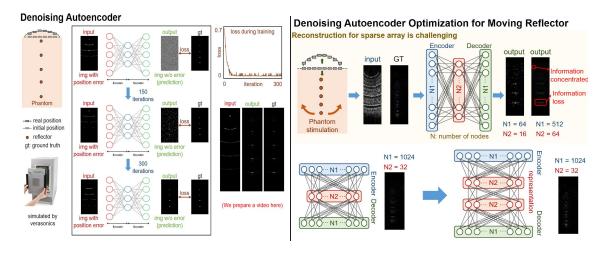
Carotid Artery Phantom Simulation



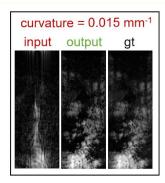
For the next step, we will keep collecting and simulating more data and try to increase the diversity of our dataset.

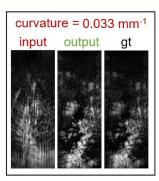
2. Establish a six-layer autoencoder to remove the noise in ultrasound B-mode image

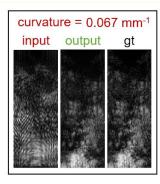
We built a six-layer autoencoder via Pytorch and try it on the sample five-reflector quick dataset. The primary results show that the autoencoder approach can be used to remove the position noise though the training dataset is so sample and the overfitting could happen, we also try to modify the parameters (number of layers and number of nodes) of our six-layer model to get the best performance:



We then add more different shape noise to the system and try to train our model on the carotid arteries dataset, we have already done the convex and concave test with random curvatures and the results are good:







Currently, we are working on sinusoidal shapes noise and already got some positive primary result, our next step is to try to use convolutional layers to increase our model's performance and do more training.

3. Learn the mechanism of YOLO and try some examples of object detection

YOLO divides the image into regions and calculates probabilities of each region. Every region is wrapped by a weighted bounding box. We simply made some examples using YOLO to make sure of its speed and accuracy.



Fig. 4 Soccer Players Image & a CT image

YOLO hasn't been applied to our project since we need to simulate the dataset and reconstruct the output from the autoencoder before classifying.

8. Team member contribution

Xinyu Tian:

- 1. Simulating dataset
- 2. Denoise Autoencoder design and training

Yudong Diao:

- 1. Established some examples of object detection using YOLO
- 2. Denoise Autoencoder design and training

References

- [1] Redmon, Joseph, and Ali Farhadi. YOLOv3: An Incremental Improvement. 2018, YOLOv3: An Incremental Improvement, pjreddie.com/media/files/papers/YOLOv3.pdf.
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- [7] Pang S, Ding T, Qiao S, Meng F, Wang S, Li P, et al. (2019) A novel YOLOv3-arch model for identifying cholelithiasis and classifying gallstones on CT images. PLoS ONE 14(6): e0217647. https://doi.org/10.1371/journal.pone.0217647