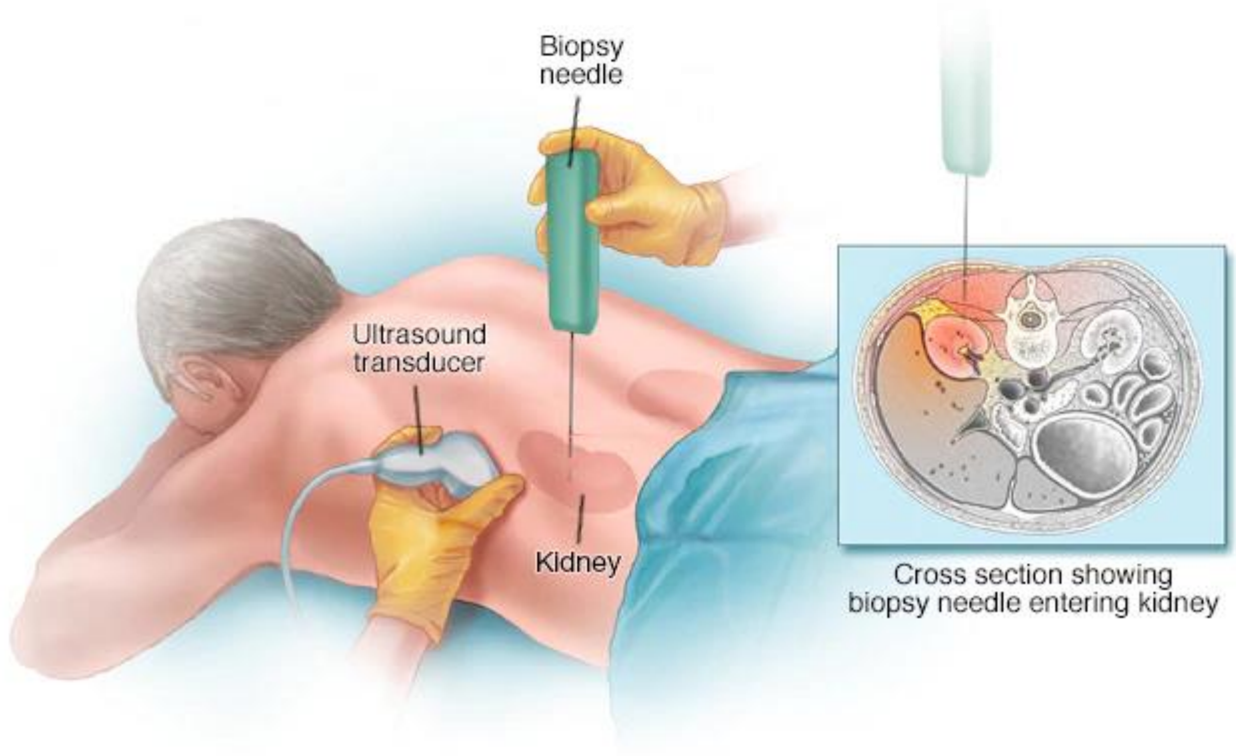
Robot-assisted steady ultrasound imaging enabled by deep learning

Group 7

Tian Xie

Mentors: Dr. Mahya Shahbazi, Dr. Emad Boctor, Dr. Russell Taylor

Background



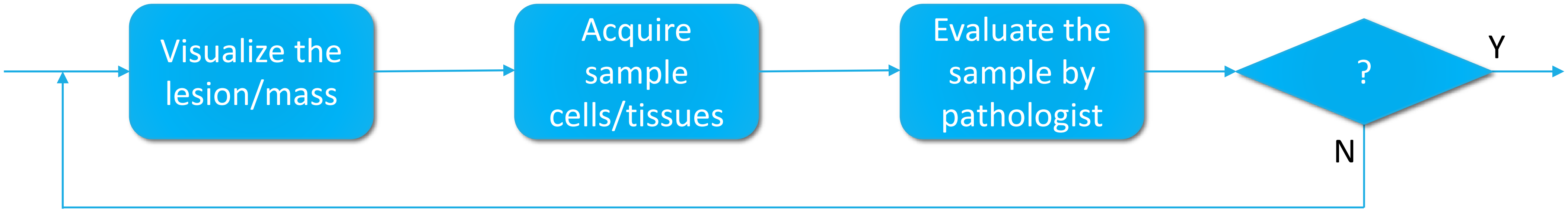
© MAYO FOUNDATION FOR MEDICAL EDUCATION AND RESEARCH. ALL RIGHTS RESERVED.

(https://www.mayoclinic.org/tests-procedures/needle-biopsy/about/pac-20394749)

Background

Tumor biopsy guided by ultrasound(US) images.

Procedure of biopsy with pathologists in room:



Consistent view of the lesion/mass must be obtained to acquire samples from several areas.

A tedious and cumbersome task to hold the US probe during the whole biopsy session.

Objectives and significance

A robot-assisted system to provide steady ultrasound imaging.

The robot will hold the probe and navigate.

The whole procedure will be more efficient and less cumbersome for sonographers.

In this project :

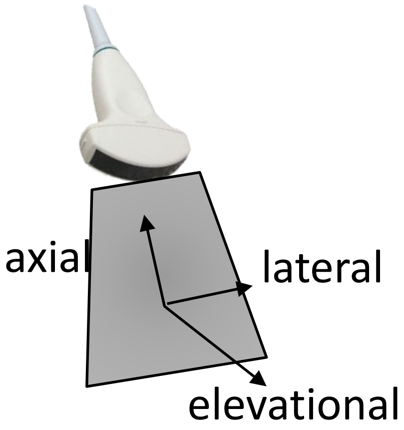
- Collect data (neighboring images, force alteration and the whole volume)
- Train the neural network to model the in-plane and out-of-plane motion in a very small range (based on speckle decorrelation in neighboring US images)
- Augment the NN into the control loop to realize servoing
- Locate and navigate to the specified slice given the neighboring images

Literature review

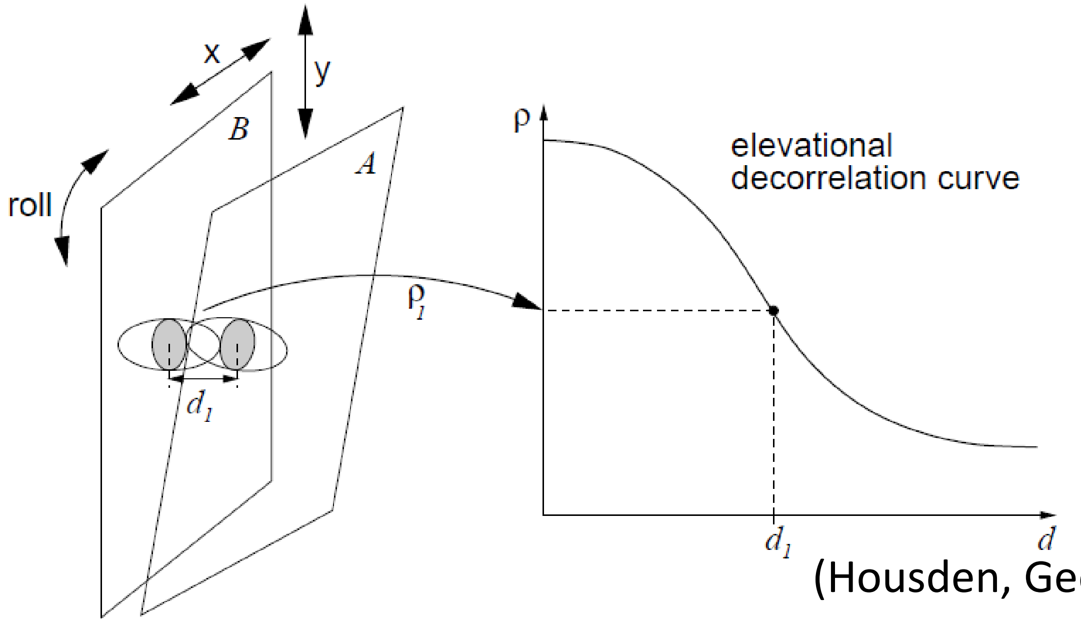
In-plane motion: can be estimated by conventional 2D image registration (G. Treece *et al* 2002).

Out-of-plane motion: elevational motion can be estimated by **speckle decorrelation.**

Fully developed speckles, so poor accuracy especially with real tissues.



coordinate

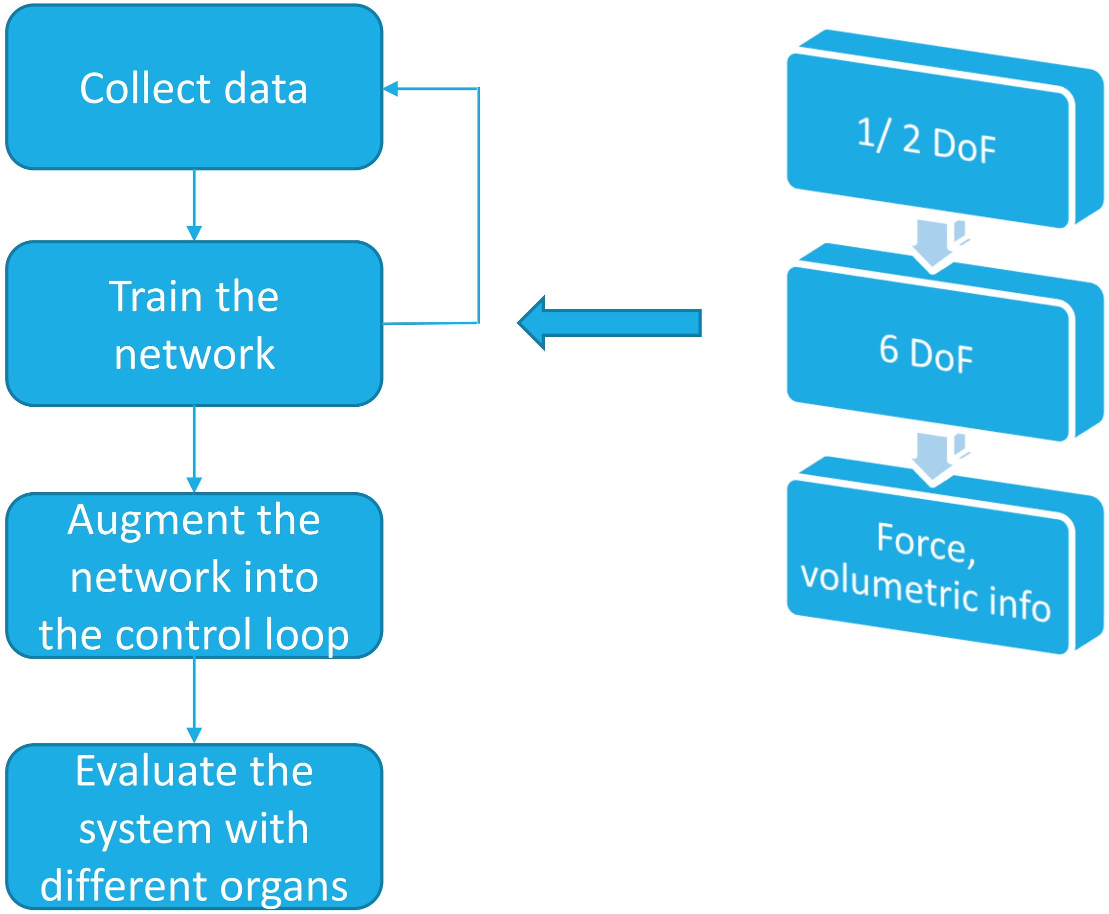


(Housden, Gee, Treece, & Prager, 2007)

Approach: workflow

Workflow

Implement deep learning to find ΔF between two images in the robot frame for servoing.



Approach: data collection

Data collection

Testbed design and setup:

- Step size: ~ 0.02mm, 0.02deg
- Range: ~ 2cm, +/- 1 deg

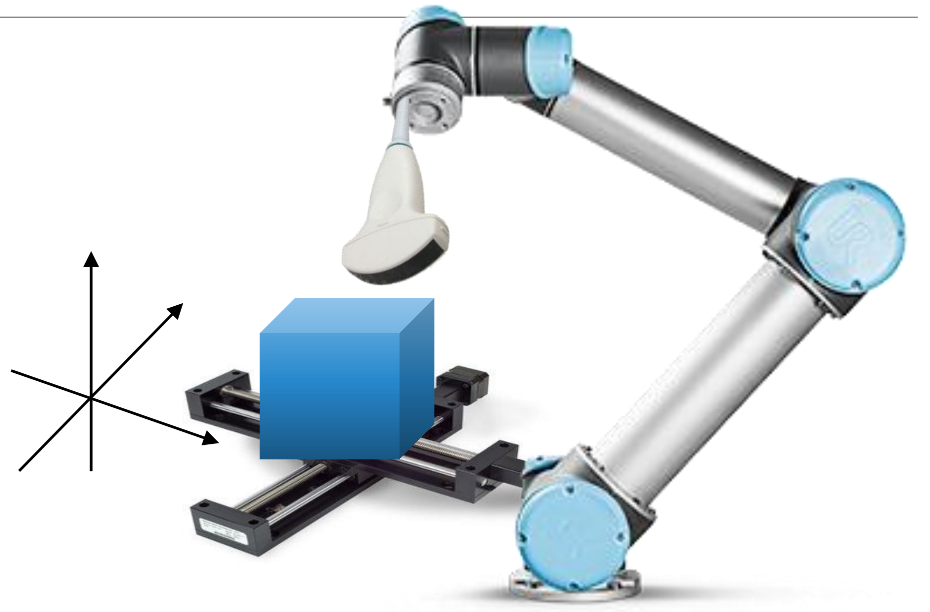
Equipment:

- UR5
- Ultrasound system (Probe attached to UR5)
- Linear stage (accuracy: 0.001mm)
- Phantoms/animal organs in a water tank attached to the linear stage

First, move the linear stage for axial, lateral and elevational motion.

Second, use UR5 for 6 DoF?

Finally, add in force sensor readings, and the volumetric scan.

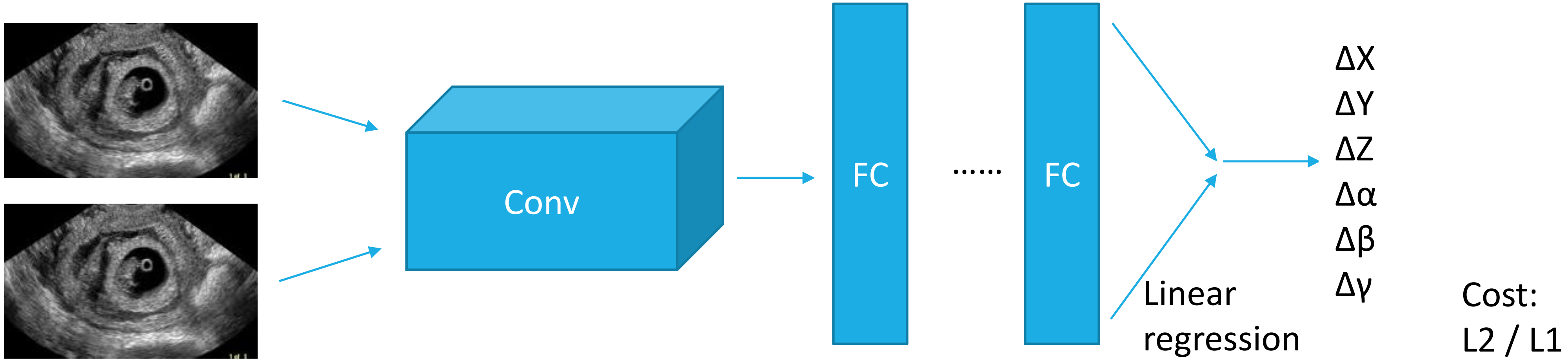


Probe still, but trivial motion of the organs

Approach: CNN for data processing

Convolutional Neural Network (CNN) for data processing

- Input: two neighboring US images
- Output: SE(3) ΔF between two images in the tool tip (probe) frame
- Modify existing CNN (AlexNet, VGG) to prove its feasibility
- A recent study (Prevost, Salehi, & Wein 2017) shows the potential of using CNN to improve accuracy
- Hierarchical parameters regression (Miao, Wang & Liao 2016)



Approach: servoing

Servoing

- Error (ΔX, ΔY, ΔZ, $\Delta\alpha$, $\Delta\beta$, $\Delta\gamma$) given by the result calculated in the NN
- Augment this Error into the control loop
- Generate control signal to move UR5
- Details will be planned after the validation of the NN

List of dependencies

Dependency	Solution	Alternatives	Status	Due	If not met?
Phantoms/ animal organs	Start with phantoms in the lab	Use 3D ultrasound data provided by Dr. Marius	Phantoms solved; rest not yet	Feb 15	/
UR5	In the lab Provided by Dr. Boctor		Solved	/	/
Ultrasound system	Provided by Dr. Boctor		Solved	Feb 15	/
3D ultrasound data	Follow up with Fereshteh and/or Reza	Collect volumetric data myself	Not yet		
Computation power	e.g. Google cloud engine		Not yet	Mar 1	Iteration of NN training will be slowed down
(3DoF) **Linear stage**	Dr. Taylor	Use UR5	Not yet	Feb 22	UR5 cannot meet the resolution (~ 0.02mm)
Optical tracker (if needed for calibration)		EM tracker	Not yet		

Deliverables

Minimum: (robotic) experiment testbed and initial data acquisition on multiple phantoms

Expected: development and evaluation of the NN to accurately model in-plane and out-of-plane motions based on correlations between neighbouring images

Maximum: augmenting the NN into the control loop of the robot for motion compensation and evaluating the system on different types of organs

Schedule

	Feb 4	Feb 11	Feb 18	Feb 25	Mar 4	Mar 11	Mar 18	Mar 25	Apr 1	Apr 8	Apr 15	Apr 22	Apr 29	May 6	May 10
Background reading, plans	■	■	■												
Testbed setup			■	■	■	■									
Data collection					■	■	■	■							
Training NN						■	■	■	■	■	■				
Augment NN into control loop											■	■	■		
Evaluation						■		■			■			■	■
Final report													■	■	■

Milestones

Early March: Testbed setup

Early April: A good amount of data

April 20: a trained neural network

May 5: control loop with NN

Management plan

Group meeting with mentors

- every Friday

File management:

- Initial data collected: JH box
- Code: GitHub

Reading list

H. Rivaz, R. Zellars, G. Hager, G. Fichtinger, & E. Boctor. (2007). *9C-1 beam steering approach for speckle characterization and out-of-plane motion estimation in real tissue*. Paper presented at the *2007 IEEE Ultrasonics Symposium Proceedings,* 781-784. doi:10.1109/ULTSYM.2007.200

R. J. Housden, A. H. Gee, G. M. Treece, & R. W. Prager. (2007). *Sensorless reconstruction of unconstrained freehand 3D ultrasound data*doi://doi.org/10.1016/j.ultrasmedbio.2006.09.015

G. M. Treece, R. W. Prager, A. H. Gee, & L. Berman. (2002). *Correction of probe pressure artifacts in freehand 3D ultrasound* doi://doi-org.proxy1.library.jhu.edu/10.1016/S1361-8415(02)00080-4

R. Prevost, M. Salehi, J. Sprung, R. Bauer, & W. Wein. (2017). *Deep Learning for Sensorless 3D Freehand Ultrasound Imaging.* Medical Image Computing and Computer-Assisted Intervention − MICCAI 2017. MICCAI 2017.

Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., & Lecun, Y. (2014). Overfeat: Integrated recognition, localization and detection using convolutional networks. In *International Conference on Learning Representations (ICLR2014), CBLS, April 2014* [http://openreview.net/document/d332e77d-459a-4af8-b3ed-55ba, http://arxiv.org/abs/1312.6229]

N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway, & J. Liang. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning?*IEEE Transactions on Medical Imaging, 35*(5), 1299-1312. doi:10.1109/TMI.2016.2535302

S. Miao, Z. J. Wang, & R. Liao. (2016). A CNN regression approach for real-time 2D/3D registration. *IEEE Transactions on Medical Imaging, 35*(5), 1352-1363. doi:10.1109/TMI.2016.2521800

W. J. Wilson, C. C. Williams Hulls, & G. S. Bell. (1996). Relative end-effector control using cartesian position based visual servoing. *IEEE Transactions on Robotics and Automation, 12*(5), 684-696. doi:10.1109/70.538974

……