Checkpoint:
Robot-assisted steady ultrasound imaging (enabled by deep learning)

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Project Overview

- Robot-assisted ultrasound system which provides steady ultrasound imaging:
  - Estimate transformation between two neighboring images via deep learning
  - Keep track of the target slice via "visual servoing"

Previous Schedule

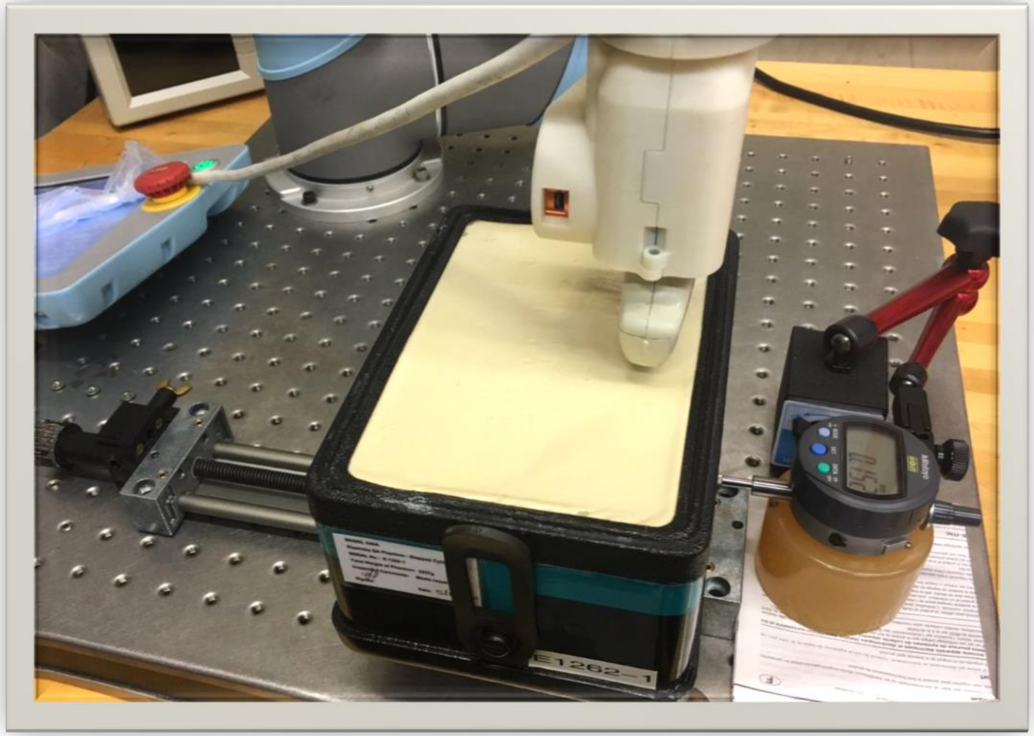
	Feb 4	Feb 11	Feb 18	Feb 25	Mar 4	Mar 11	Mar 18	Mar 25	Apr 1	Apr 8	Apr 15	Apr 22	Apr 29	May 6	May 10
Background reading, plans															
Testbed setup				w/ UR5											
Data collection															
Training NN						1,2 DoF						?			
Augment NN into control loop															
Evaluation															
Final report															

Work UpToDate

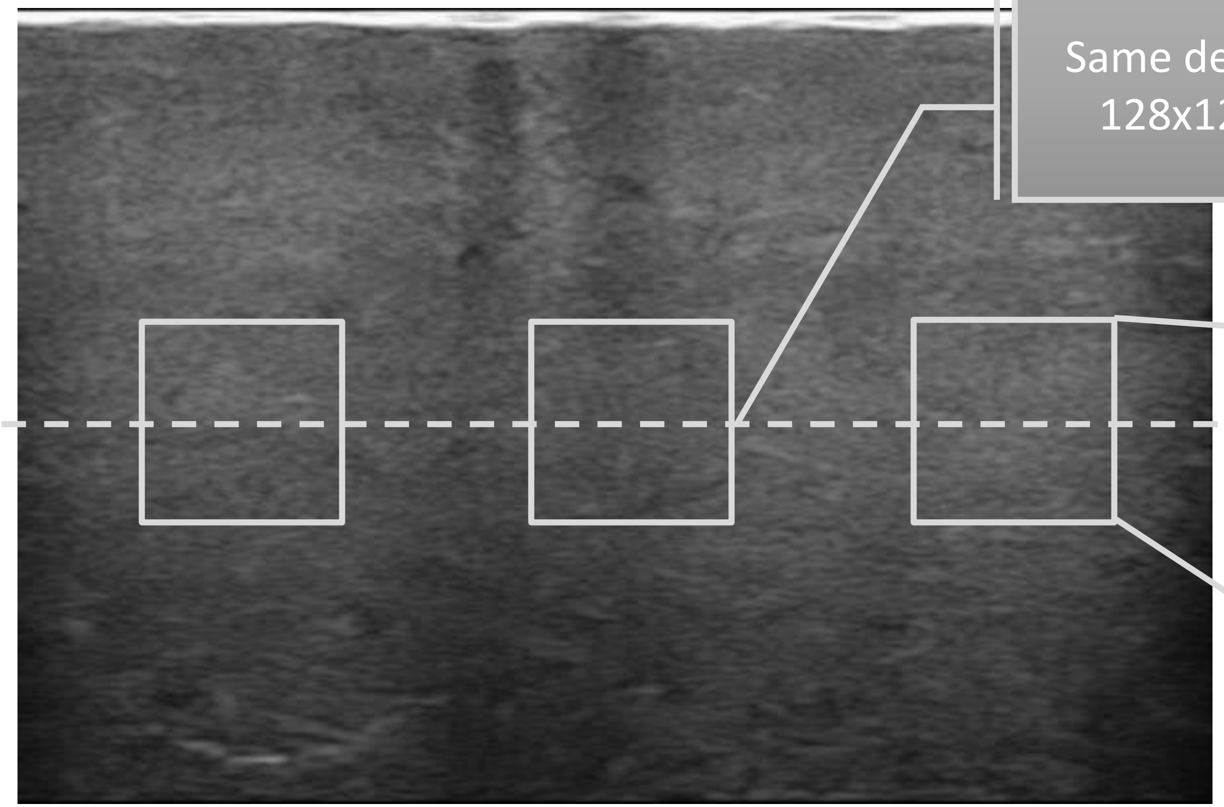
- Experiment setup
- Data acquisition
- Neural network with 1 DoF (Standard CNN, two-channel input)
- Neural network with 2 DoF (Similar to SCNN, two independent inputs, multi-task training)

Experiment Setup

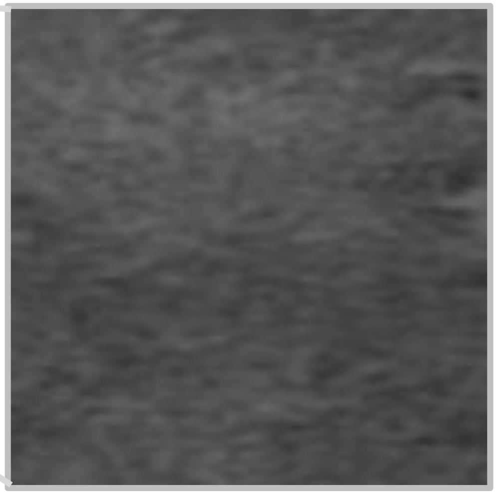
	w/ UR5	w/ linear stage
Equipment	UR5, Ultrasonic system	Linear stage, dial indicator + holder, UR5, Ultrasonic System
Range & resolution	Elevational: [0,1] mm, 0.2mm Lateral: [-5,5] mm, 0.2mm	Elevational: [0,1] mm, 0.02mm
Pros	Fast, massive acquisition	High resolution (measurement 0.001mm)
Cons	Poor resolution (0.2mm) Error	Slow 1D only w/ the current linear stage

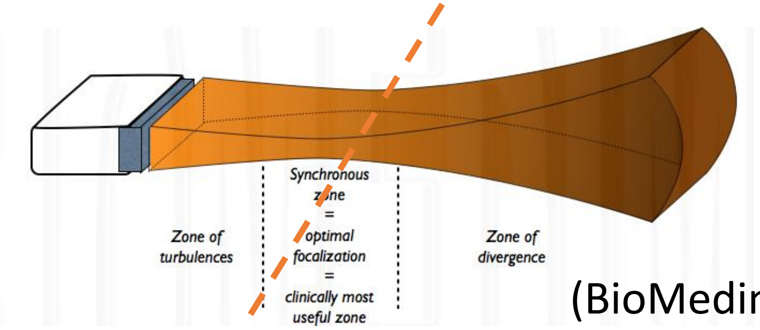


Data: US images



Same depth
128x128





(BioMedima)

Robot pose (ground truth): [x, y, z, r1, r2, r3]
/ Dial indicator reading

Two CNN structures

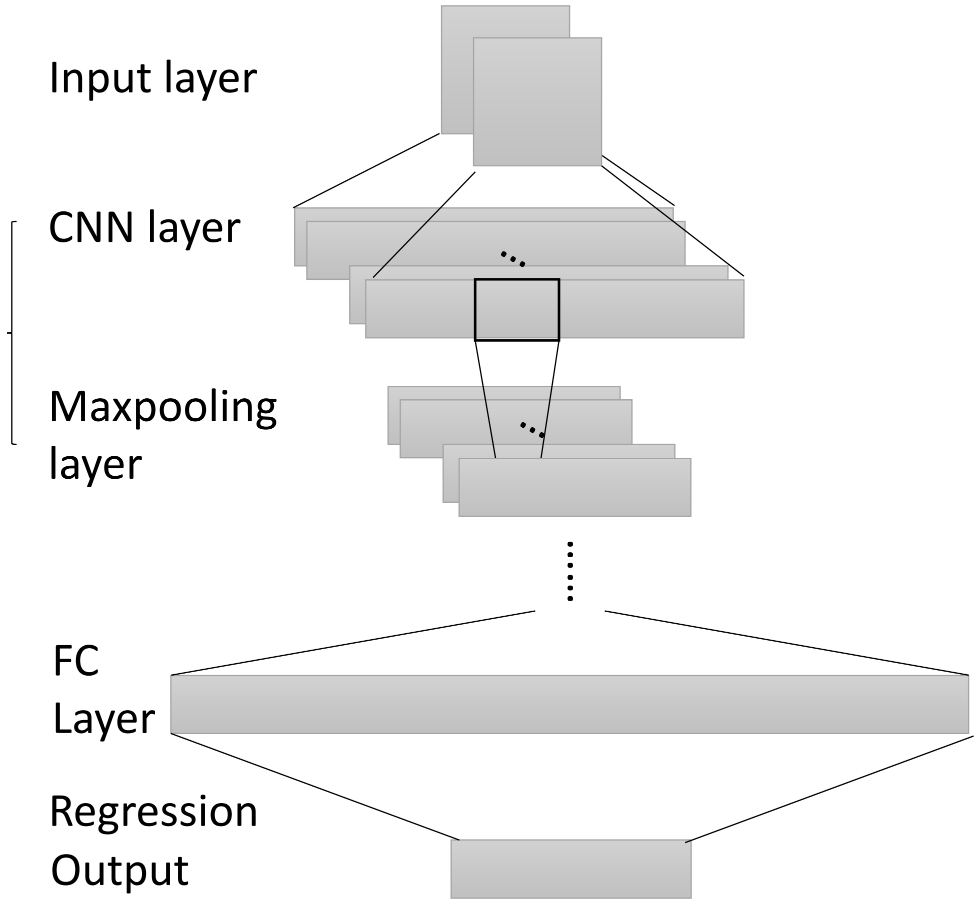


Fig 1. Standard CNN

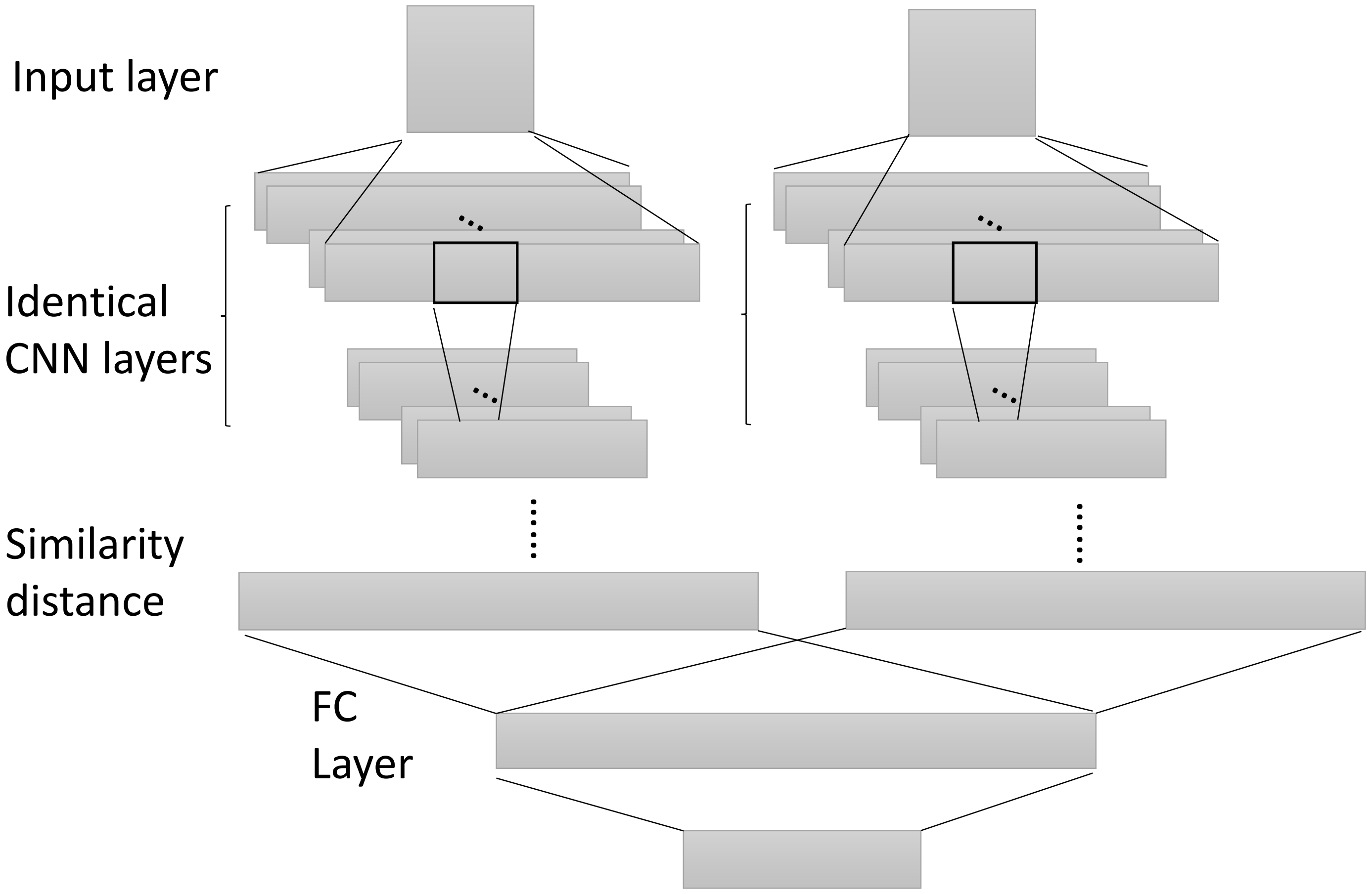
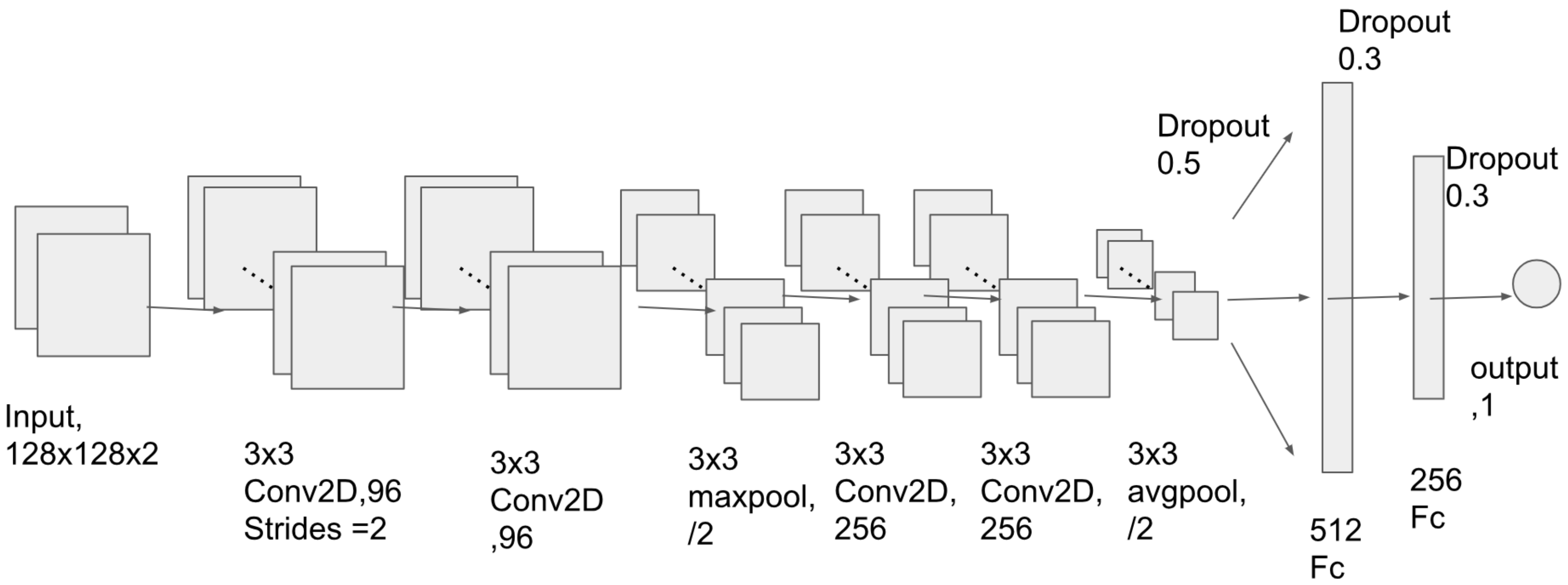


Fig 2. Siamese CNN [1]

The 1st CNN structure

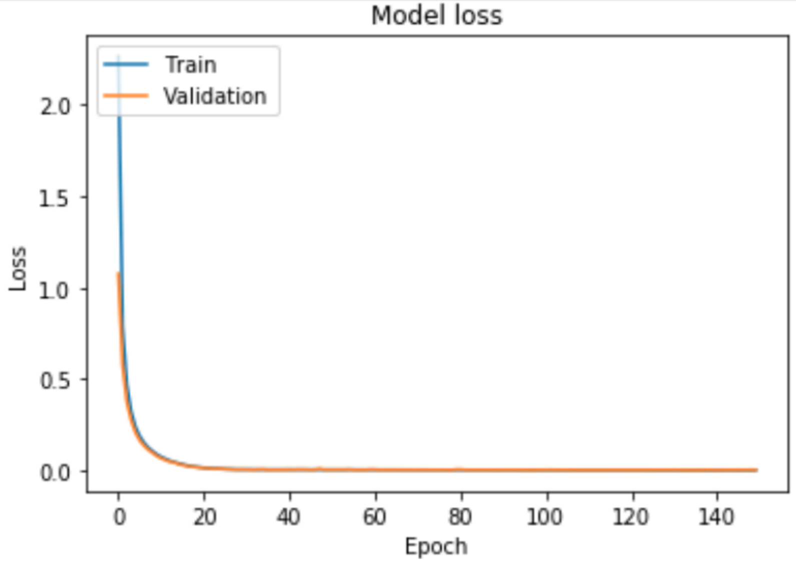


- **Cost function: log(cosh(h(x)-y))**
  - Compared with Mean Absolute Error: better performance for large distances
  - Compared with Mean Square Error: less sensitive to outliers
- **Optimizer: Adam**

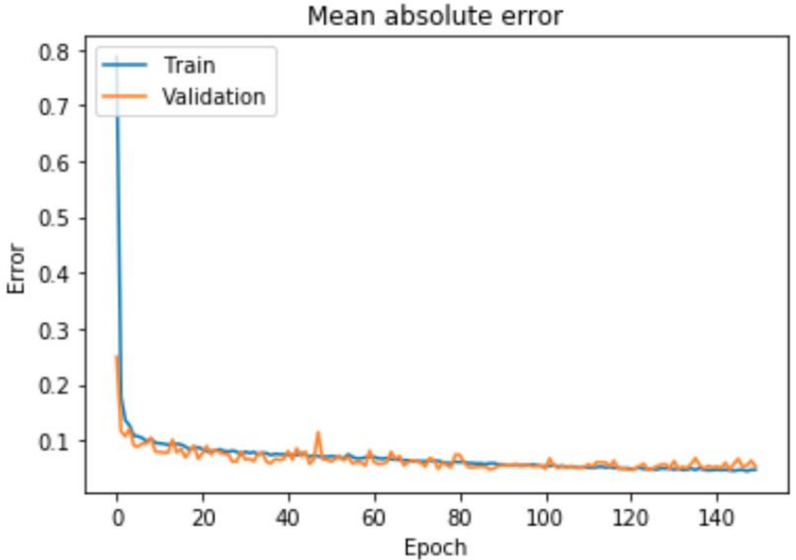
Input data – 1 DoF

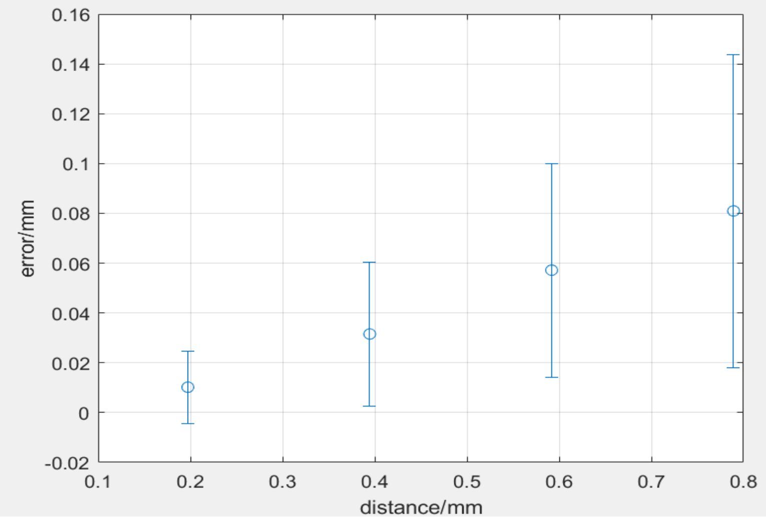
- Elevational distance: 0 – 1 mm. (Correlation ~ 0.5 at 1mm)
- Training set: 10,336 pairs of neighboring images from one phantom
- Validation set: 1,149 different pairs of neighboring images from the same phantom and same region
- Test set: 1) 1,050 pairs of images from the same phantom but different regions; 2) 50 pairs from the other CIRS elasticity phantom

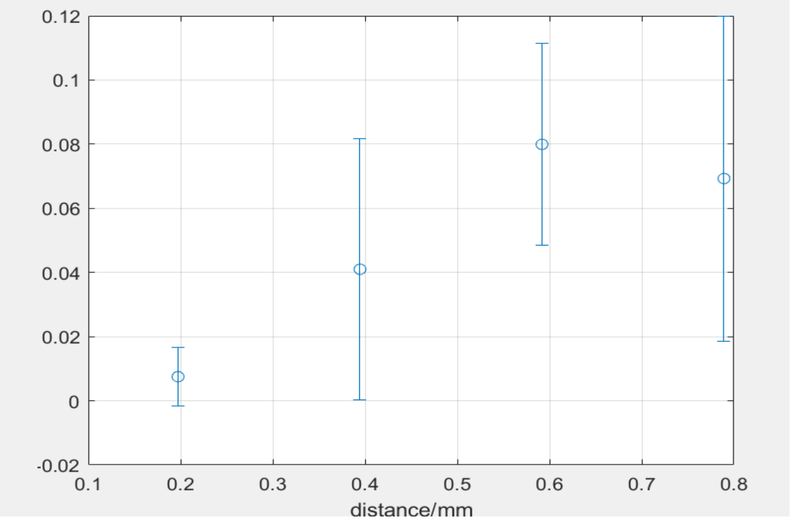
Results



	Logcosh Loss	Mean abs error (mm)	Mean % error
Train	0.0037	0.0474	
Validation	0.0045	0.0534	
Test different region	0.0034	0.0446	8.25%
Test the other phantom	0.0032	0.0458	8.37%







Input data – 2 DoF

- Elevational distance:[0, 1] mm. (Correlation ~ 0.5 at 1mm)
- Lateral distance: [-5, 5] mm.
- Training set, validation set and test set are from different regions of the same phantom

Results

- ~~Output 2 DoF~~:
  - the model does not converge

- Train on images w/ 1 DoF, test on images w/ 2 DoF
  - Table 1
  - Estimation ~ maximum distance of the training
  - Only when lateral translation is small (<0.4mm), the elevational estimation is close to ground truth
- Train on images w/ 2 DoF, test on images w/1 DoF
  - Table 2
  - Better results than Table 1

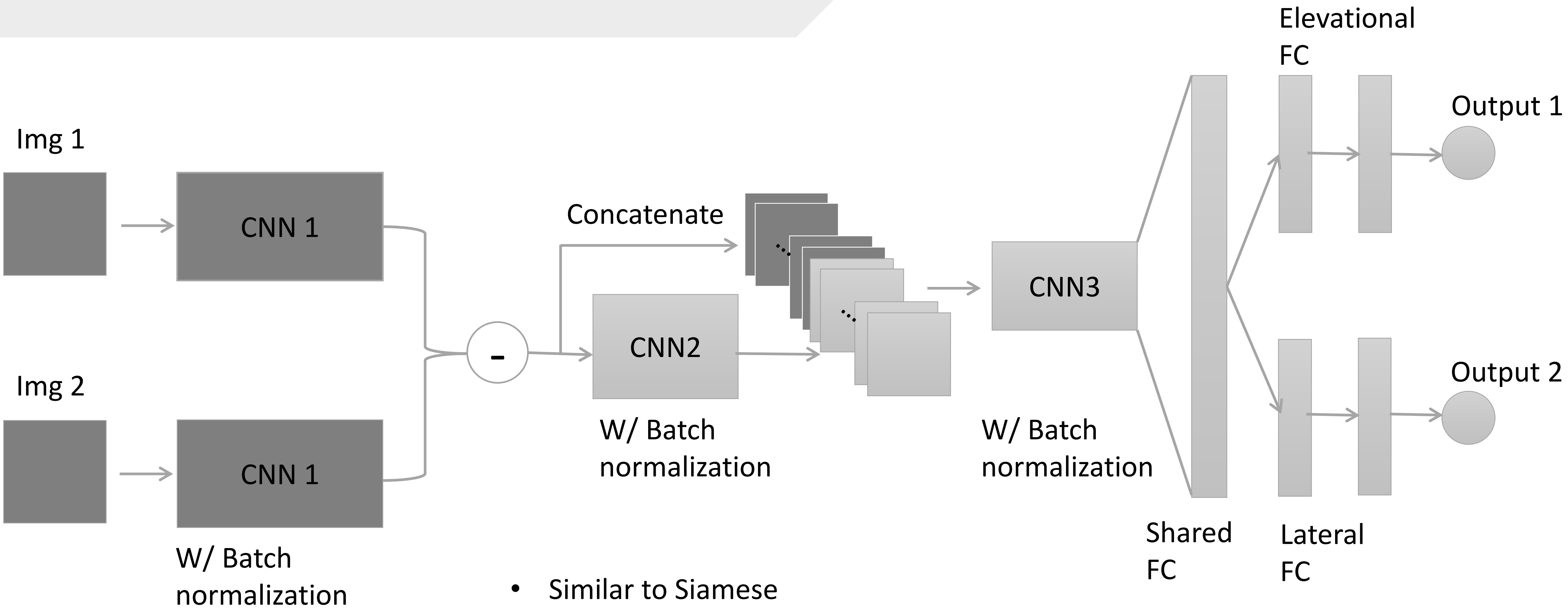
	Logcosh (after 50 epochs)	MAE (mm) (after 50 epochs)
Train set	0.0059	0.0712
Test set	0.1529	0.5119

Table 1

	Logcosh (after 50 epochs)	MAE (mm) (after 50 epochs)
Train set	0.0083	0.0757
Test set	0.0119	0.1008

Table 2

The 2nd CNN structure



- Similar to Siamese
- Multi-task learning
- Cost function: MAE + Logcosh
- Optimizer: Adam

Results

- Train set:
  - MAE of elevational translation: 0.0496 mm (range: 0 - 1 mm)
  - MAE of lateral translation: 0.1036 mm (range: -5 - 5 mm)

- Test set: (different regions)
  - MAE of elevational translation: ~ 0.15 mm
  - MAE of lateral translation: ~ 1.4mm (!!!)

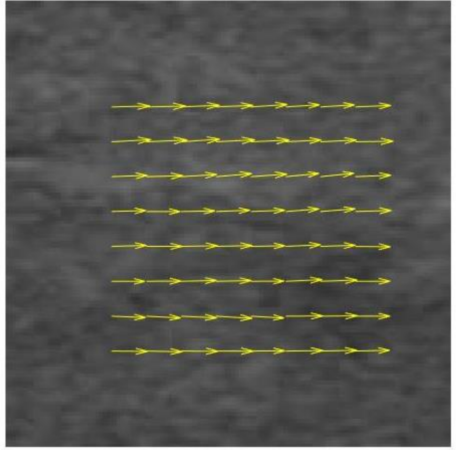
Overfit!

Lack of common features among random speckles

Next Steps

- Current issues and solutions
- New deliverables
- New schedule
- New list of dependencies

Current Issues & solutions



Conventional Image Region tracking for in-plane motion

↓

CNN for elevational translation

↓

Estimate transformation:

T_in_plane * T_out_of_plane

Conventional method in CV:

- Image region tracking technique (Hager and Belhumeur, 1998) [2]
- $\mu = (u_x, u_y, \gamma)'$:
  $pixel\ translation\ and\ rotation$

Minimize:

$$O = \|I(\mu, t) - I(0, t0)\|^2$$
$$\delta\mu = -M^{\dagger}(I(\mu, t+\tau) - I(0, t0))$$
$$\mu(t+\tau) = \mu(t) + \delta\mu$$

Iterate until convergence ($\|\delta\mu\| < \epsilon$)

New deliverables

Minimum: (robotic) experiment testbed and initial data acquisition on ~~multiple~~ phantoms	On calibration phantom On animal tissues/ other phantoms after proof of feasibility	Apr 28
Expected: development and evaluation of the NN to ~~accurately model in-plane~~ and out-of-plane motions based on correlations between neighbouring images	1) Report of the feasibility of NN to do this task; 2) Development of a pipeline combining conventional methods (in-plane, 3DoF) and the neural network (out-of-plane translation, 1DoF)	Apr 28
Maximum: augmenting the NN into the control loop of the robot for motion compensation and evaluating the system on different types of organs	Transformation estimation with 6 DoF; Motion compensation for 2 DoF	May 9

Carry out at the same time

New schedules (starting from Mar 25)

	Mar 31	Apr 7	Apr 14	Apr 21	Apr 28	May 5	May 12
Testbed setup w/ linear stage and dial indicator							
Feasibility of CNN only							
Conventional Methods							
Pipeline to combine CNN and conventional methods (4 DoF)							
6 DoF estimation							
Visual servoing 2DoF							
Final report							

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
Linear stage, dial indicator	Dr. Taylor	Use UR5	Not yet	Feb 22	UR5 cannot meet the resolution (~ 0.02mm)
Access to a 3D printer			Not yet	Mar29	

References

[1] Jane Bromley, James W Bentz, L´eon Bottou, Isabelle Guyon, Yann LeCun, Cliff Moore, Eduard S¨ackinger, and Roopak Shah. Signature verification using a siamese time delay neural network. International Journal of Pattern Recognition and Artificial Intelligence, 7(04):669–688, 1993.

[2] Hager, G., & Belhumeur, P. N. (1998). Efficient region tracking with parametric models of geometry and illumination. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20(10), 1025-1039. https://doi.org/10.1109/34.722606

Question?