Stabilized Ultrasound Imaging of a Moving Object Using 2D B-mode Images and a Convolutional Neural Network

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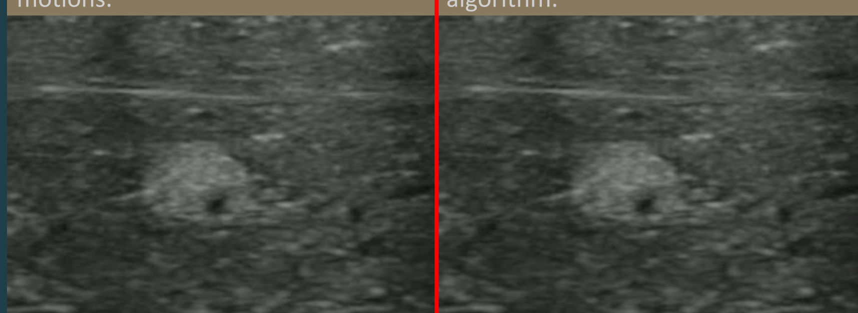
Co-robotic ultrasound + tracking algorithm
→ steady imaging

Images are subject to physiological motions.	Stabilized imaging with the tracking algorithm.



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Outline

MUSiiC Research Laboratory

Challenge and Motivation — In a biopsy, compensate **physiological motions** and reduce **musculoskeletal trauma** for sonographers using **co-robotic** ultrasound

Methods — 6-DoF motion estimation. A **convolutional neural network** is embedded to estimate **out-of-plane motions**. Joint velocities control.

Evaluation and Results — Feasibility of the tracking algorithm within simulation environments built with scans obtained on **biopsy phantoms**, **pork**, etc.

Discussion and Conclusions — Advantages. Limitations.

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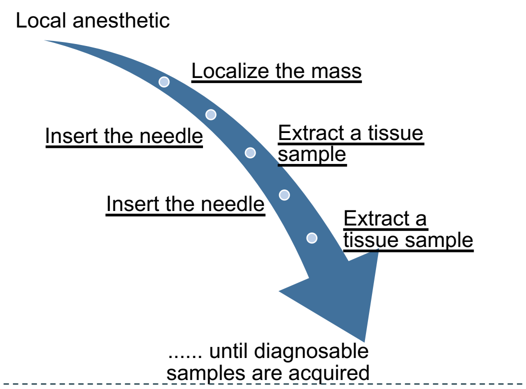
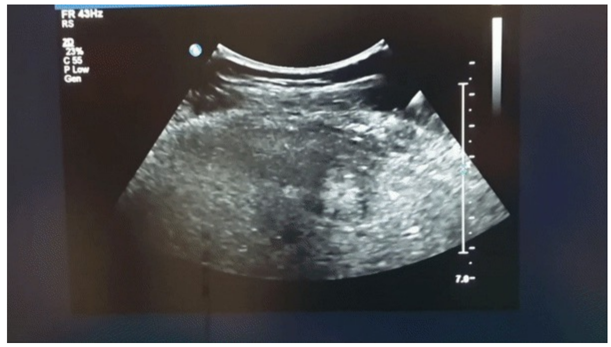
Challenge: A Biopsy Procedure

- An ultrasound-guided biopsy





Ultrasound-guided liver biopsy on a 47-year-old female patient[1].

[1] Courtesy of https://www.youtube.com/watch?v=2SIZOqJiUt4

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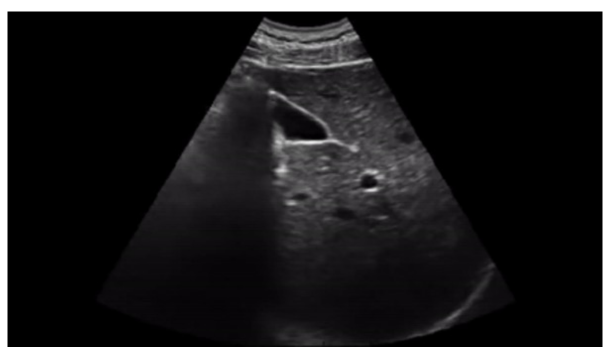
Challenge: Physiological Motions

- Imaging of abdominal organs is subject to physiological motions:
  - Respiratory motion
  - Cardiac-induced motion
  - Patient's small movement
- Amplitudes of motions:
  - E.g. Shimizu et al.[3] investigated liver tumor motion using high-speed MRI
  - 21 mm, 8 mm, 9mm in the SI, AP and lateral directions.



Ultrasound sequence of liver undergoing respiratory and cardiac - induced motion[2].

[2] Courtesy of https://www.youtube.com/watch?v=NkDTNnvCtl4
[3] Shimizu, S., Shirato, H., Xo, B., Kagei, K., Nishioka, T., Hashimoto, S., & Miyasaka, K. (1999). Three-dimensional movement of a liver tumor detected by high-speed magnetic resonance imaging. Radiotherapy and oncology, 50(3), 367-370.

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Challenge: Work-related Musculoskeletal Disorders (WRMSD)

Main causes of WRMSD[5]

An accumulation of repeated exposure to physical risk factors:

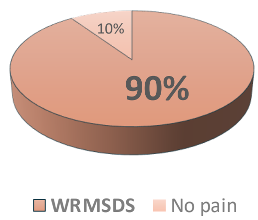
- Awkward or sustained postures

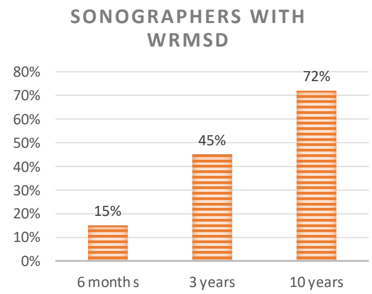
- Repetition
- Force

- Contact pressures

(Murphey, S., 2017).

2,963 participants in Evans *et al.*[4]





[4] Evans, K., Roll, S., & Baker, J. (2009). Work-related musculoskeletal disorders (WRMSD) among registered diagnostic medical sonographers and vascular technologists: a representative sample. Journal of Diagnostic Medical Sonography, 25(6), 287-299.
[5] Murphey, S. (2017). Work related musculoskeletal disorders in sonography.

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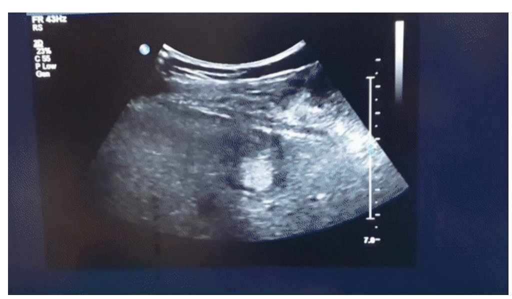
Motivation

- **Robotic arm:**
  - force control, accuracy, repeatability
- **Co-robotic ultrasound**

"Hand-over-hand control"

In a biopsy procedure, **physiological motions** of the target is another problem to solve.



Respiratory motion

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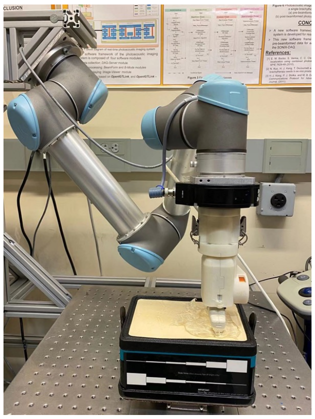
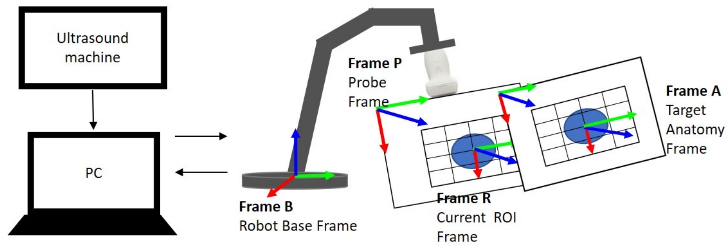
Proposed Method: System Setup



Co-robotic setup



Tracking algorithm for stable imaging

- In-plane motion: $\Delta g_{pr}(t) = g_{pr}(0)\, g_{pr}^{-1}(t)$
- Out-of-plane motion: $\Delta g_{ar}(t)$
- 6 degree of freedom (DoF) motion: $\Delta g_{p_O p} = g_{pr}(0)\left(g_{pr}(t) g_{ar}^{-1}(t)\right)^{-1}$
- Proportional control on SE(3) error

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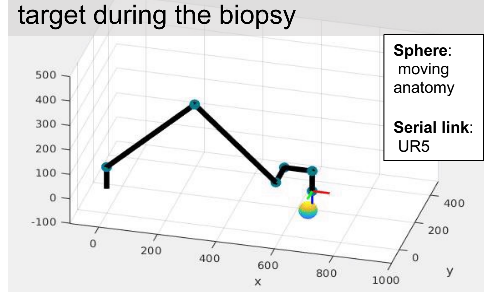
Proposed Method: Significance

A co-robotic ultrasound system with a tracking algorithm

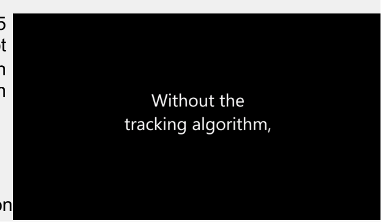
- **compensates physiological motions:**
  - keep track of the target frame
  - suppress motion artifact and enhance image quality
- **reduces musculoskeletal injuries for sonographers:**
  - use a robot for long-lasting procedures
  - integrate with force control
- **requires only B-mode images:**
  - apply to almost all commercial ultrasound machines

Have a robotic system to track the target during the biopsy



➊UR5 Robot motion simulation

➋Imaging comparison



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Overview: Tracking Algorithm

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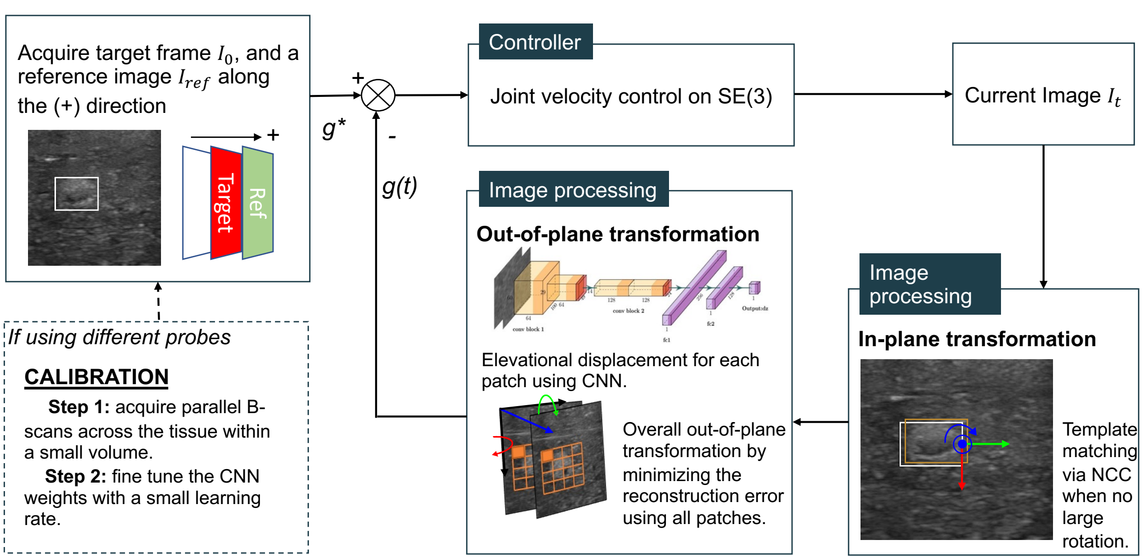

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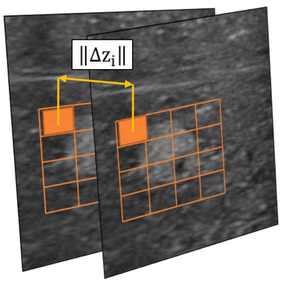
Estimation of Out-of-plane Motion

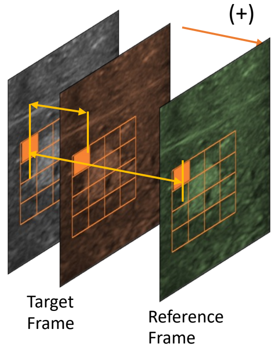
(1)

Use a CNN to estimate the unsigned distance between two patches



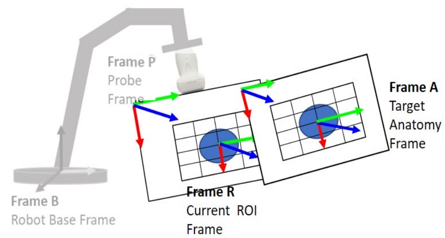
(2)

Get the sign using both the target and reference frames



(3)

Fit the overall out-of-plane transformation using all patches



$$g_{ar} = argmin\,\Sigma\left\|g_{ar}\vec{P}_{r,i} - \vec{P}_{a,i}\right\|$$

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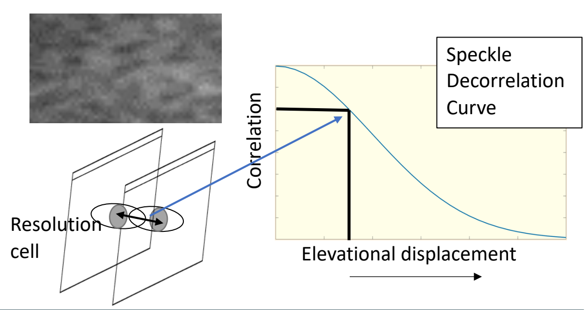
Speckle Decorrelation

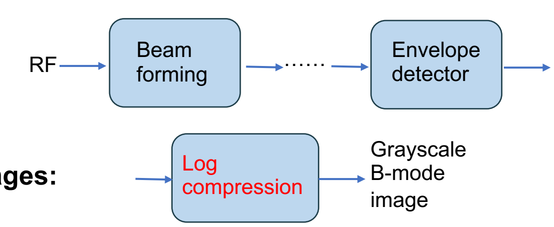
Speckle
- Granular appearance in ultrasound images
- Diffuse scattering in a resolution cell

Speckle decorrelation
- Imperfect focus along the elevational direction → neighboring patches are correlated
- Gaussian using RF signals and assuming Gaussian resolution cell



Conventional speckle decorrelation methods[6]**:**
- RF signals may not be accessible
- Hard to convert back to RF signals
- Rely on fully developed speckles

Our method only requires grayscale B-mode images:
- High non-linearity of the CNN
- "Correlation"



[6] Gee, A. H., Housden, R. J., Hassenpflug, P., Treece, G. M., & Prager, R. W. (2006). Sensorless freehand 3D ultrasound in real tissue: speckle decorrelation without fully developed speckle. *Medical image analysis*, *10*(2), 137-149.

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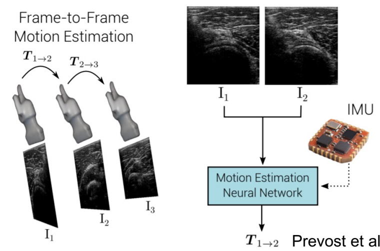
CNN to Estimate Elevational Distance

Prevost et al.[7] 3D freehand ultrasound estimation using **deep learning**

- Is used for tomography
- Depends on anatomical features of the specific part of the body (e.g. forearm)

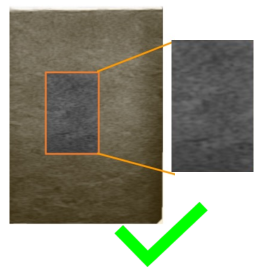


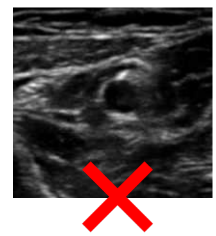
Prevost et al., 2018

In a tracking scenario, the target appearance varies.

A model invariant to the appearance of the masses.

Training data containing only speckle noises without anatomical features (e.g. vessels).





[7] Prevost, R., Salehi, M., Jagoda, S., Kumar, N., Sprung, J., Ladikos, A., ... & Wein, W. (2018). 3D freehand ultrasound without external tracking using deep learning. *Medical image analysis*, *48*, 187-202.

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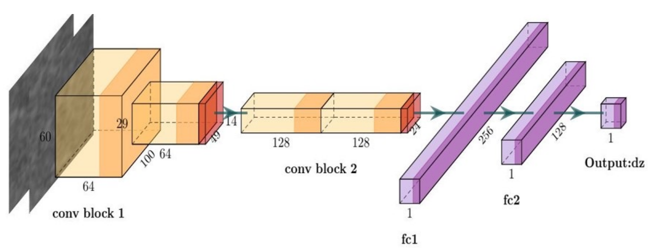
CNN Architecture

- <u>A standard convolutional neural network</u>
- # of parameters: ~ 2.7 million
- **Real-time** tracking**.** Less than **50 ms** on a PC with an NVIDIA GTX 1050 Ti GPU (use 16 pairs of patches)
- **Input**: two neighboring B-mode image patches
- **Output**: elevational distance between two patches



Conv block
Conv layer Batch normalization Conv layer Batch normalization Maxpooling

<u>Optimizer:</u>
Adam
<u>Loss function:</u>
Logcosh (more robust to outliers compared with MSE)

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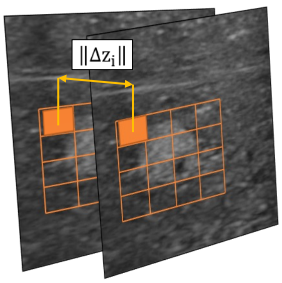
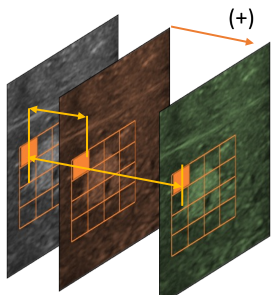
Estimation of Out-of-plane Motion

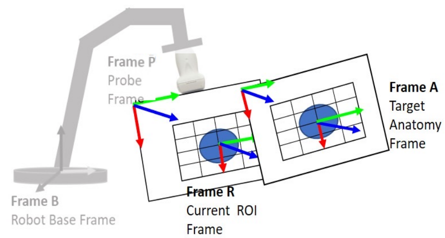
(1) Use a CNN to estimate the unsigned distance between two patches



(2) Get the sign using both the target and reference frames



(3) Fit the overall out-of-plane transformation using all patches



$$g_{ar} = argmin\,\Sigma\left\|g_{ar}\vec{P}_{r,i} - \vec{P}_{a,i}\right\|$$

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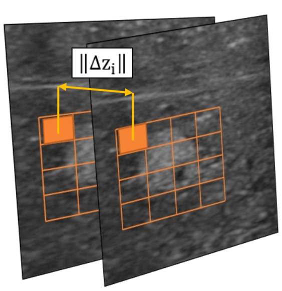

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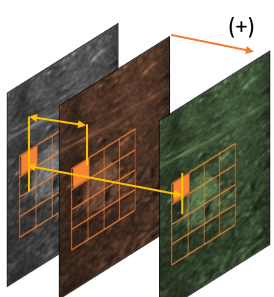

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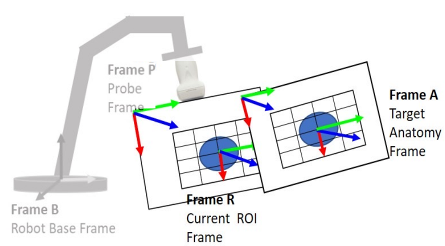

$$g_{ar} = argmin\,\Sigma\left\|g_{ar}\vec{P}_{r,i} - \vec{P}_{a,i}\right\|$$

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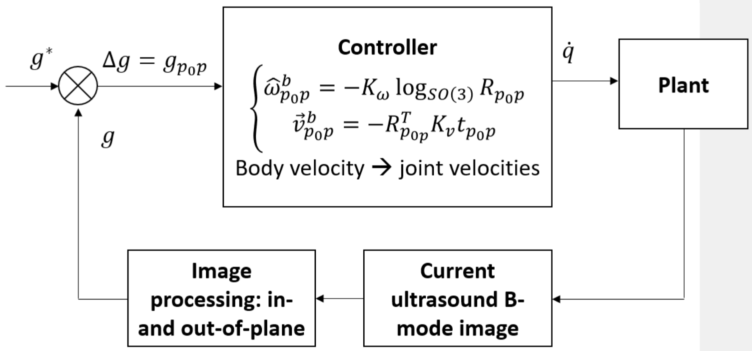
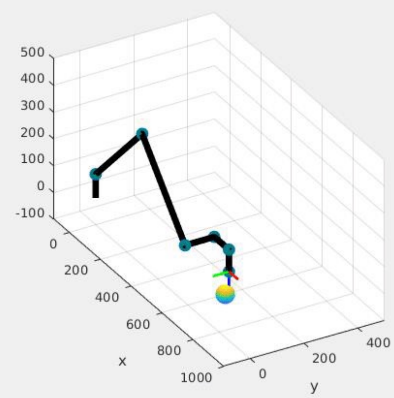
Velocity Control on SE(3) Group

- Implement a proportional (P) controller with double-geodesic feedback on SE(3)[8]





Robot simulation of one experiment using pork images.

[8] Bullo, F. and Murray, R. M., (1995). Proportional derivative (PD) control on the Euclidean group.

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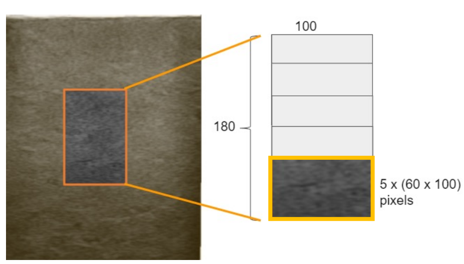
Data and Experiments

CNN Training Data

- **Patch size**: 60 x 100 pixels
- **Patches contain only speckle noises**
- Elevational displacement (ground truth) ranges from **0 to 1 mm** (close to the size of a resolution cell)



- Sonix-Touch Q+ Ultrasound machine (Ultrasonix Inc., Richmond, BC, CA)
- Probe: BK L14-5/38 linear, 10 MHz
- Phantoms: CIRS Elasticity QA phantom model 049 and 049A
- Ground truth: linear stage + a dial indicator (0.001mm)
- 12,000 pairs: 80% for training, 20% for validation
- 2,000 patches collected on the other phantom for testing

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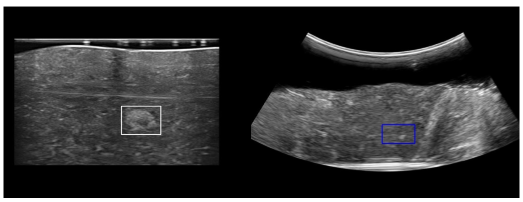
Data and Experiments

Data

- Sonix-Touch Q+ Ultrasound machine
- Probes:
  - (1) BK L14-5/38 linear; (2) C5-20/60 curvilinear
- Phantoms:
  - (a) CAE Blue Phantom tissue biopsy ultrasound training model
  - (b) Pork tenderloin



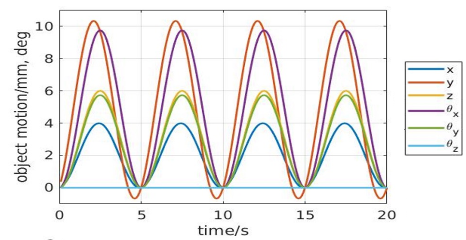
(a) (b)

Motion Simulation

- Construct a volume using parallel scans
- Simulate cyclic motions
- Implement P control to track the moving target

$$x(t) = \frac{A}{2} - Acos^{2n}\left(\frac{\pi t}{\tau} - \phi\right)$$

$$\alpha(t) = \theta \sin^2\left(\frac{\pi t}{\tau} - \phi\right)$$



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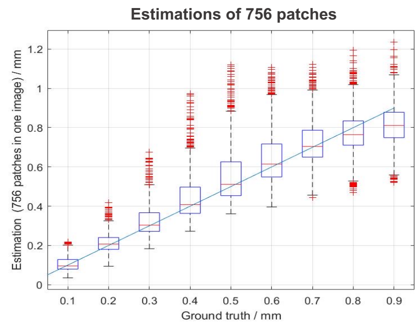
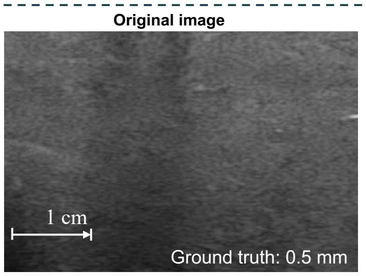
Evaluation and Results: CNN Estimation

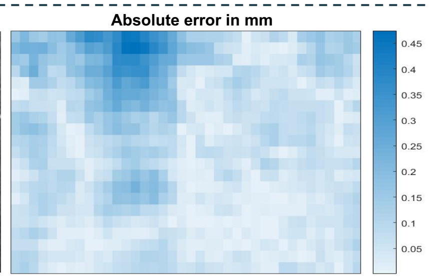
- 10 parallel scans with 0.1 mm separation
- 756 patches in one image (slide by 20 pixels along x, y axes)
- Accurate estimations in range 0.2 to 0.7 mm
- Poorer estimations near 0 or 1 mm (near the size of the resolution cell)



Mean absolute percentage error

Ground truth/mm	Mean abs %
0.1	10.56
0.2	**1.62**
0.3	**0.49**
0.4	**0.29**
0.5	**0.95**
0.6	**2.23**
0.7	**0.25**
0.8	5.4
0.9	9.99





- Label each pixel with the absolute error computed at the nearest patch center
- Dark regions correspond to non-fully developed speckles ("bad" regions for speckle decorrelation)

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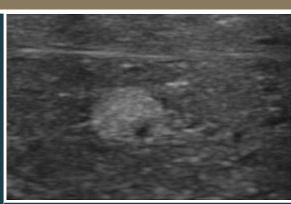
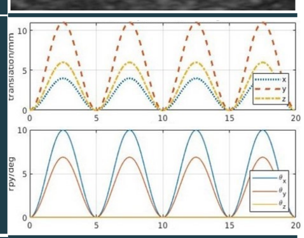
Evaluation and Results: Biopsy Phantom

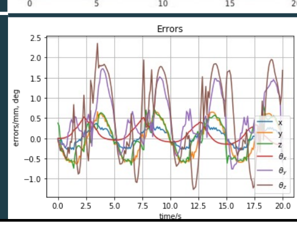
Target view



Target motion

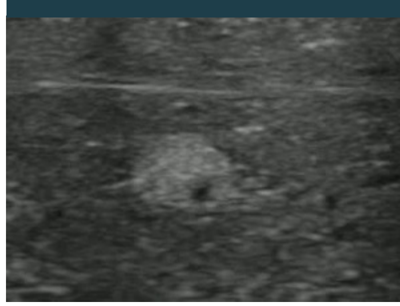


Errors over time



- **Target motion:**
  - 4, 11 and 6 mm along axial, lateral and elevational axes
  - 10 and 6 degree about x and y axes (w/o in-plane rotation)
- **Error:**
  - Translations: less than 0.7 mm
  - Rotations: less than 2 degree
- No fine tuning. Same linear probe used for CNN training.

No tracking



With tracking

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Evaluation and Results: Biopsy Phantom

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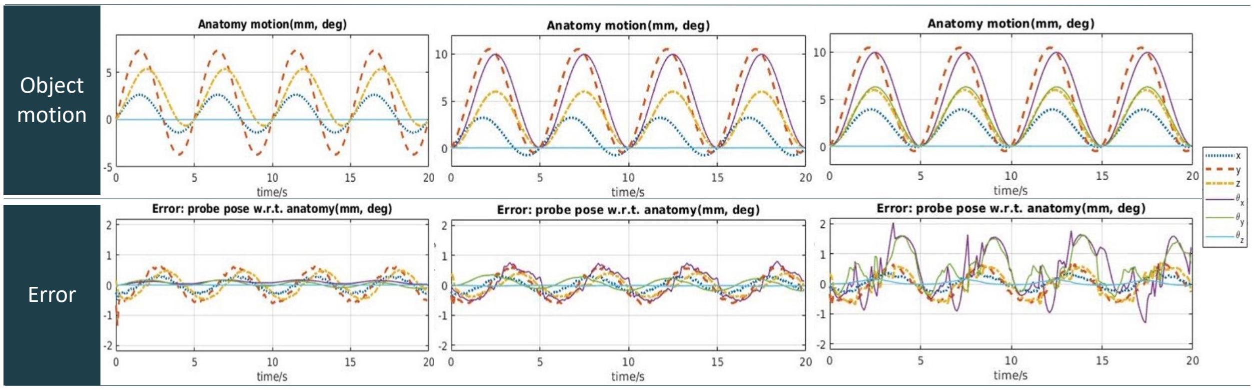
- **Target motion:**
  - 4, 11 and 6 mm along axial, lateral and elevational axes
  - Less than 10 degree about x and y axes (w/o in-plane rotation)
  - Different random phase angles
- **Low errors compared with the magnitudes of the motions.**



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Evaluation and Results: Pork Tenderloin

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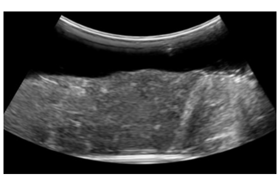
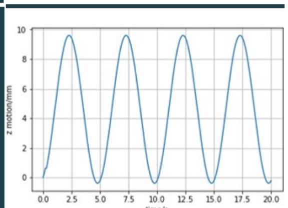
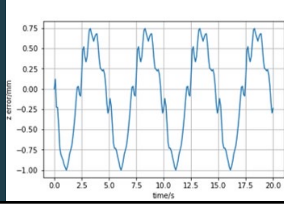
Target view



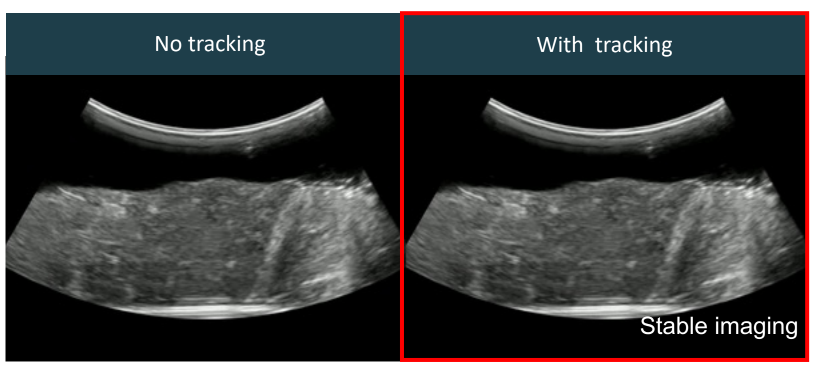
Target motion



Error over time



- **Target motion:**
  - 1-DoF elevational translation (amplitude 10 mm)
- **Error:**
  - Less than 1.05 mm
- Fine tuning using 400 pairs of patches. 40 epochs within 40 s (GPU)



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Discussion and Conclusions

Verified the feasibility of a co-robotic ultrasound system:

- **Real-time Tracking** of a moving object using 2D B-mode images
- **Out-of-plane motion** estimation using CNN based on speckle patterns
- Velocity control on robot joints

Advantages:

- Provide stabilized imaging
- Track in real time
- Use only B-mode images
- Reduce musculoskeletal disorder for sonographers

Limitations:

- Larger deformation
- Quick and large motion – beyond the size of a resolution cell

Further development:

- Algorithms robust to in-plane rotation
- Kalman filter
- Force control

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Thank you

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Appendix 1: tracking algorithm

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Tracking algorithm

If using different probes

CALIBRATION

Step 1: acquire parallel B-scans across the tissue within a small volume.

Step 2: fine tune the CNN weights with a small learning rate.

TRACKING

Step 1: at time $t = 0$, acquire the target image I_0.

Step 2: move end effector a small distance to the (+) elevational direction. Acquire a reference image I_{ref}.

while tracking:

Step 3: compute in-plane transformation -- NCC

Step 4: estimate out-of-plane translation for each patch using the CNN

Step 5: estimate the overall out-of-plane transformation using all patches

Step 6: compute transformation error and control the robot joint velocities

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Appendix 2: P control on SE(3)

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- Implement a proportional (P) controller with double-geodesic feedback on SE(3) group [11]

Body Velocity

$$\Delta g = g_{p_0 p} = g_{pr}(0)\left(g_{pr}(t) g_{ar}^{-1}(t)\right)^{-1} \rightarrow \left(R_{p_0 P}, t_{p_0 p}\right)$$

$$\begin{cases} \widehat{\omega}_{p_0 p}^{b} = -K_\omega \log_{SO(3)} R_{p_0 p} \\ \vec{v}_{p_0 p}^{b} = -R_{p_0 p}^{T} K_v t_{p_0 p} \end{cases}$$

(Positive definite K_ω and K_v)

$$\vec{V}_{p_0 p}^{b} = \begin{bmatrix} (\widehat{\omega}_{p_0 p}^{b})^{\vee} \\ \vec{v}_{p_0 p}^{b} \end{bmatrix}$$

$$\vec{V}_{bp}^{b} = Ad_{g_{p_0 p}^{-1}} \vec{V}_{bp_0}^{b} + \vec{V}_{p_0 p}^{b}$$

(Change coordinate to the base frame)

- Omit object velocity (the first term $\vec{V}_{bp_0}^{b}$) on the R.H.S → joint velocity

Joint Velocity

$$\dot{\vec{q}} = J_b^{\dagger} \vec{V}_{bp}^{b}$$

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