Robot-assisted Steady Ultrasound Imaging and Visual Servoing Enabled by Deep Learning

Computer Integrated Surgery II

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Introduction

A robot-assisted system is developed to provide steady ultrasound imaging for the tumor biopsy. In-plane and out-of-plane motions are estimated given two successive images. The pipeline includes an image region tracking algorithm and a CNN model. Then visual servoing is integrated into the control loop to compensate the motion and regain the target image.

During a biopsy, the sonographers need to hold a probe with a static pose for around 10 to 20 minutes. The system can complete this cumbersome task for them during the whole procedure, which may help reduce the risk of getting musculoskeletal injuries for sonographers.

The Problem

- A sonographer needs to hold and press the ultrasound probe for a long time to guide the needle pass during a biopsy. This task is tedious and may lead to muscle injuries for sonographers. Robotic ultrasound is a promising solution to this problem.
- Out-of-plane motion is hard to estimate. Current methods use a speckle decorrelation curve to estimate elevational translation. The method relies on a calibration phantom with fully-developed speckles. It also involves heavy computation based on statistics of RF signals.

The Solution

- In-plane motion: use an image region tracking algorithm (Hager & Belhumeur, 1998).
- Out-of-plane motion:
  - Large motion: 2D correlation with reference planes.
  - Small motion (< 1mm): a CNN model is trained to estimate elevational translation for a small patch. Apply the model patch-wise, and then use the least median square algorithm to fit the transformation between neighboring images for all patches.
- Visual servoing: integrate ultrasound images into the control loop.

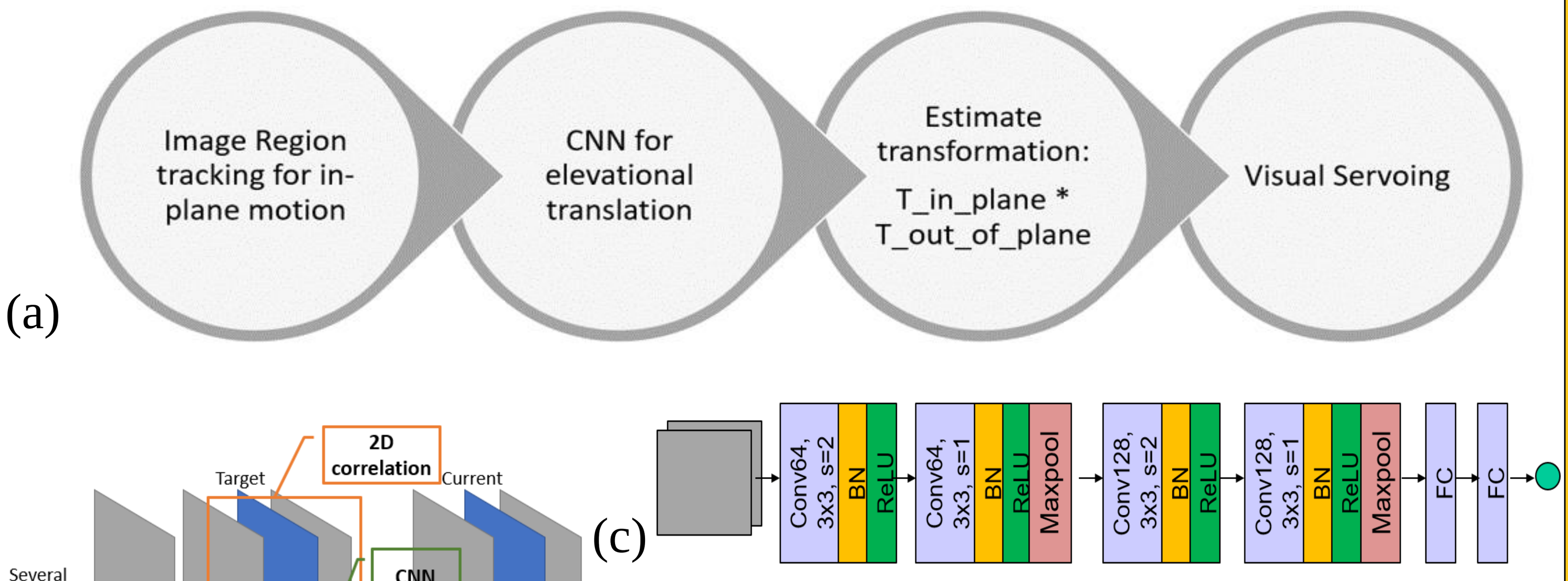
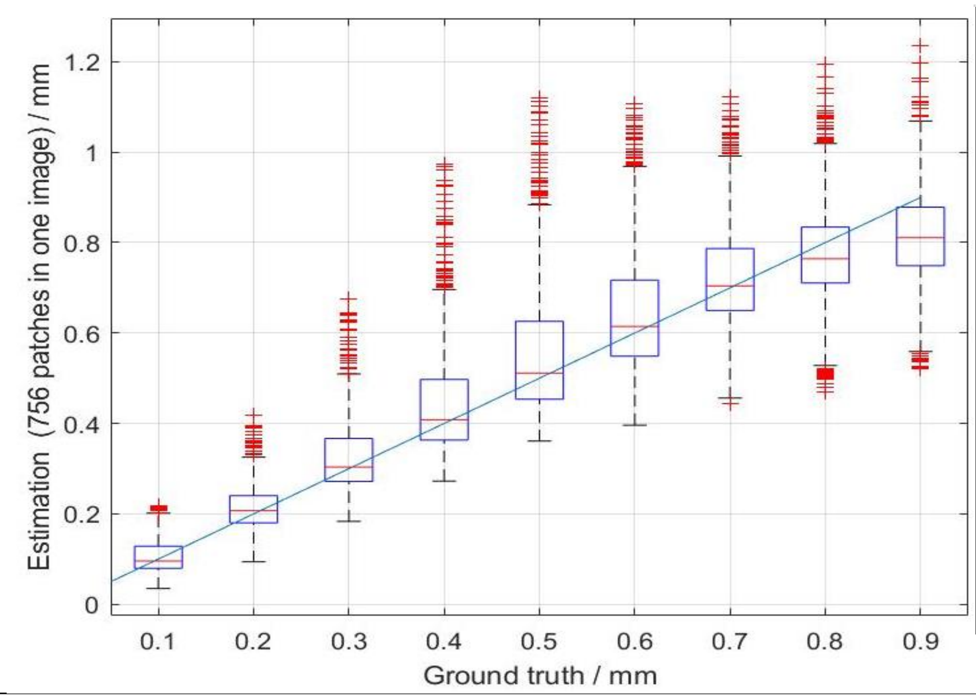


Fig 1. Solutions
(a) Workflow
(b) Out-of-plane motion
(c) CNN model
(d) Another CNN model with comparable performance

Outcomes and Results

- The CNN model estimates the elevational translation with high accuracy (Fig. 2).
- Outliers correspond to “bad” regions in the image (Fig. 3).
- Out-of-plane rotation can be estimated (Fig 4.). Evaluation of accuracy is still in progress.
- Motion compensation for 1 DoF in-plane lateral translation (Fig. 5).



Ground truth /mm	Median /mm	Variance	Mean percentage error
0.107	0.0957	0.0015	10.56%
0.204	0.2073	0.0023	1.62%
0.305	0.3035	0.0061	0.49%
0.407	0.4082	0.0145	0.29%
0.507	0.5118	0.0214	0.95%
0.601	0.6144	0.0207	2.23%
0.706	0.7042	0.0164	0.25%
0.808	0.7644	0.0144	5.40%
0.901	0.811	0.0123	9.99%

***Fig 2**. Estimation of elevational translation. (Ten images, step size: 0.1 mm.)*

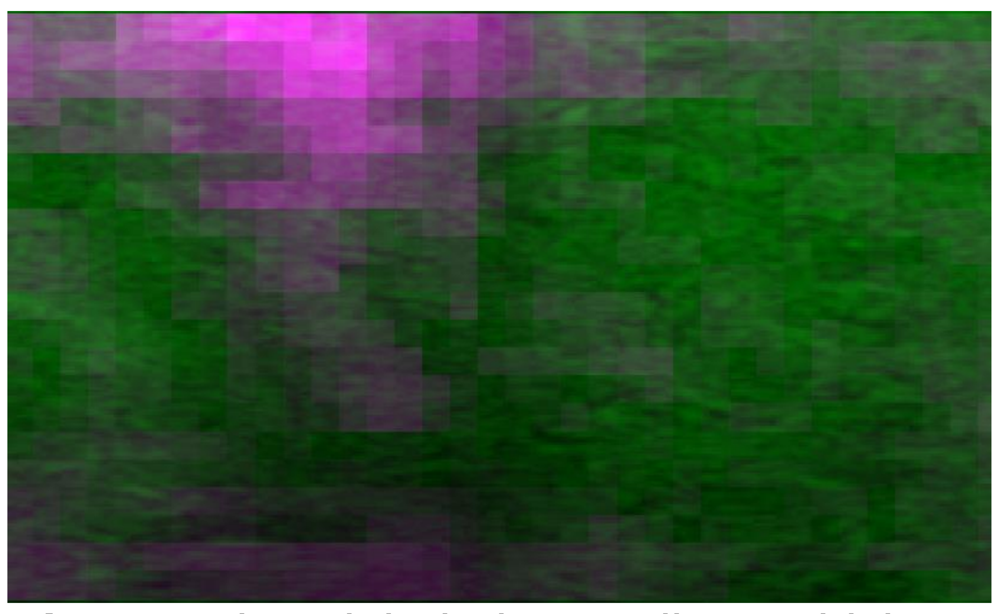


***Fig 3**.Regions labeled as outliers, which correspond to some “bad” regions in the image.*

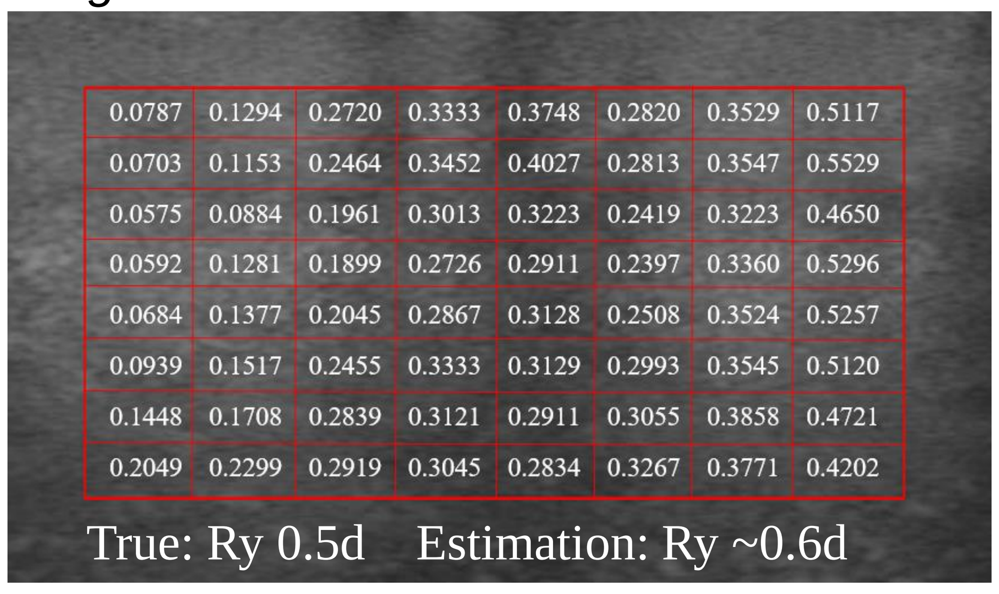


***Fig 4.** Estimate out-of-plane rotation. Fit the transformation for all patches (xi, yi, δzi).*

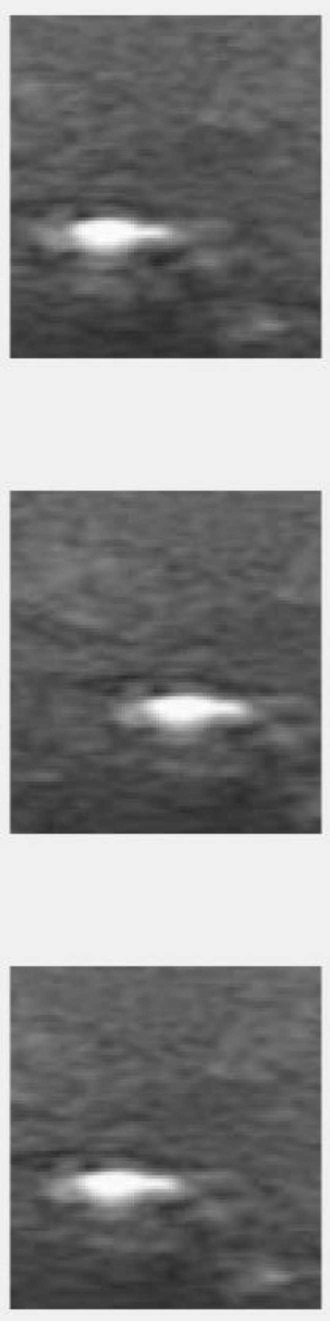


***Fig 5**. Visual servoing for in-plane lateral translation.*

Future Work

- Deep learning to detect fully-developed speckles.
- Evaluate and improve the accuracy of SE(3) estimation.
- Solve the communication and synchronization problem among systems. Real-time control. 6 DoF visual servoing.
- It will be extended to a master thesis.

Lessons Learned

- Deep learning cannot solve all your problems.

Support by and Acknowledgements

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