K-Wire Tracking in 3D Camera Views

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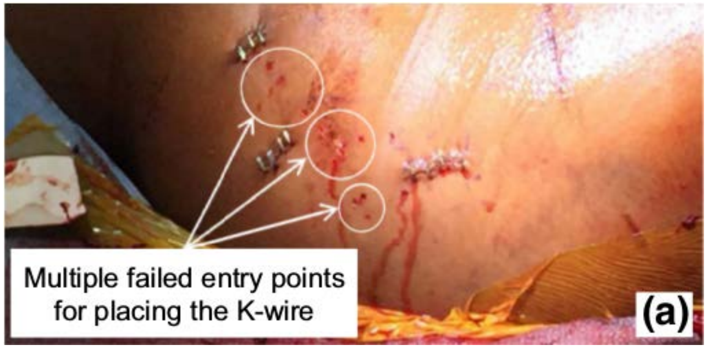
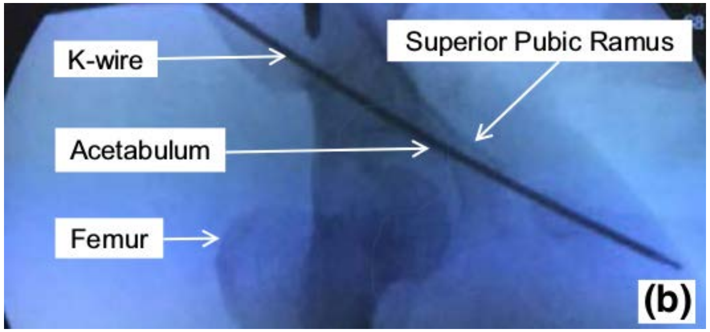
Background

- K-wire insertion currently requires many X-rays
- Misplacement could damage important structures in the body
- Current tracking solutions are ineffective for K-wire
  - Traditional computer vision solutions fail
  - Trackers cannot be placed on it
- Propose to use convolutional neural network trained on RGB images



Multiple entry wounds



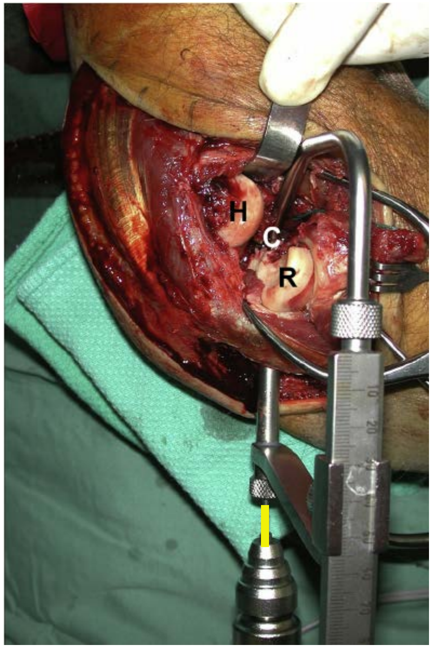
X-ray image of hip region in pelvic surgery

Images from Fischer, Marius, et al. "Preclinical usability study of multiple augmented reality concepts for K-wire placement." International Journal of Computer Assisted Radiology and Surgery 11.6 (2016): 1007-1014.

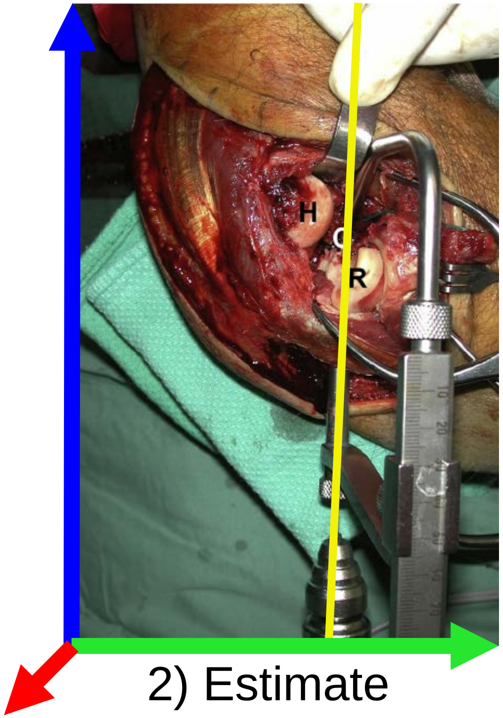
Solution

Deep learning based K-wire tracking algorithm using RGB images

- Eliminates the need for multiple X-ray images
- Can be easily integrated into augmented reality solutions to orthopedics surgery



1) Identify K-wire



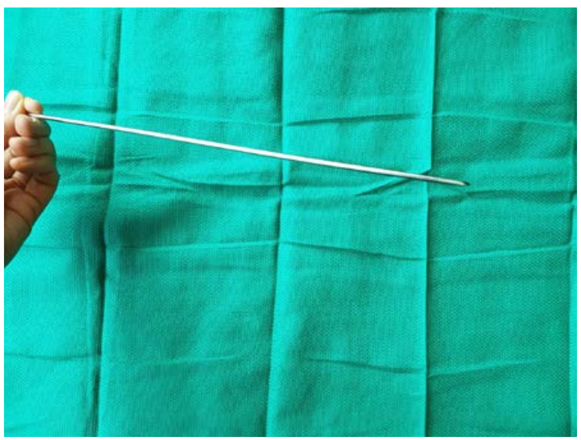
2) Estimate orientation/pose

3) Show K-wire orientation/pose

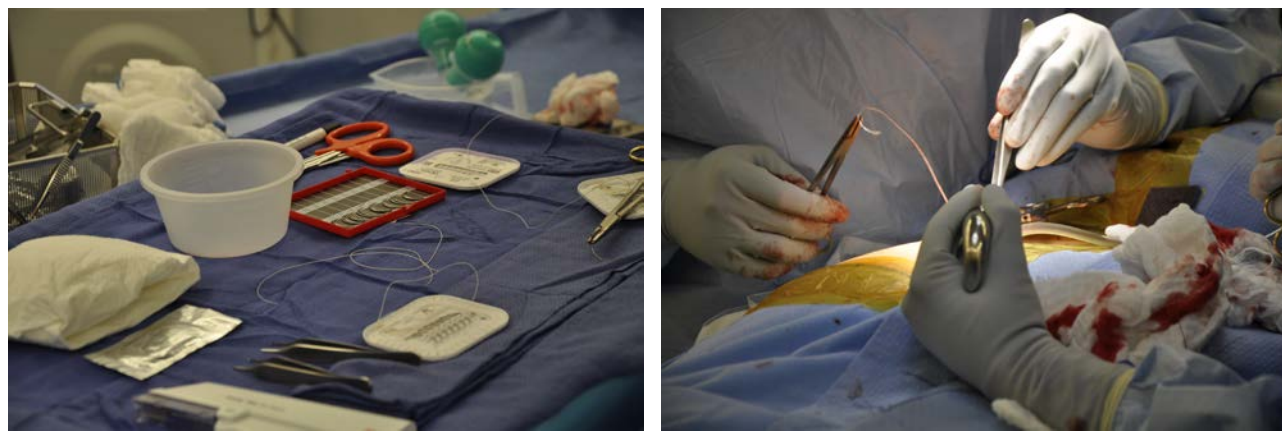
All images from Kovacevic, D., Vogel, L. A., & Levine, W. N. (2015, November). Complex Elbow Instability: Radial Head and Coronoid. Hand Clinics.

Technical Approach

- Create data
  - Create a modular data set by capturing foreground and background separately
- Design network
  - Design and train a CNN based neural net to segment K-wire in RGBD images
  - HED for tool tracking[8] , U-Net[9]...
- Pose estimation from segmented stereo image pairs



Sample foreground shot before segmentation



Sample background shots

[8] Pakhmov et. al, Semantic-boundary-driven approach to Instrument Segmentation for Robotic Surgery
[9] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In MICCAI 2015 (Vol. 9351, pp. 234–241)

Deliverables

Minimum

- Phantom to create training data
- Modular data set
  - Foreground videos with K-wire against drape
  - Segmentations of the K-wire position
- Calibrated stereo cameras
- CNN trained on K-wire video with plain background to segment it

Expected

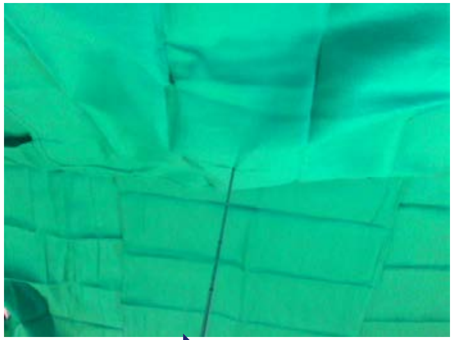
- Realistic data set of surgical workspace by composing foreground and background videos of surgical workspace with instruments (ie. scalpel)
- Algorithm to extract K-wire orientation from segmentation <u>in 2D</u>
- CNN trained with realistic data that can segment the K-wire

Maximum

- <u>Algorithm to extract K-wire position and orientation in 3D in free space</u>
- Algorithm to estimate position of K-wire <u>tip with occlusion</u>

Data Set Creation – Capturing Images

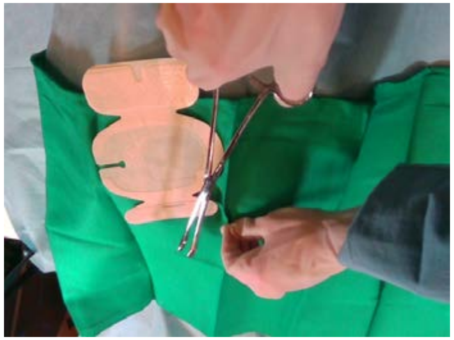
Foreground images



Varying Lighting

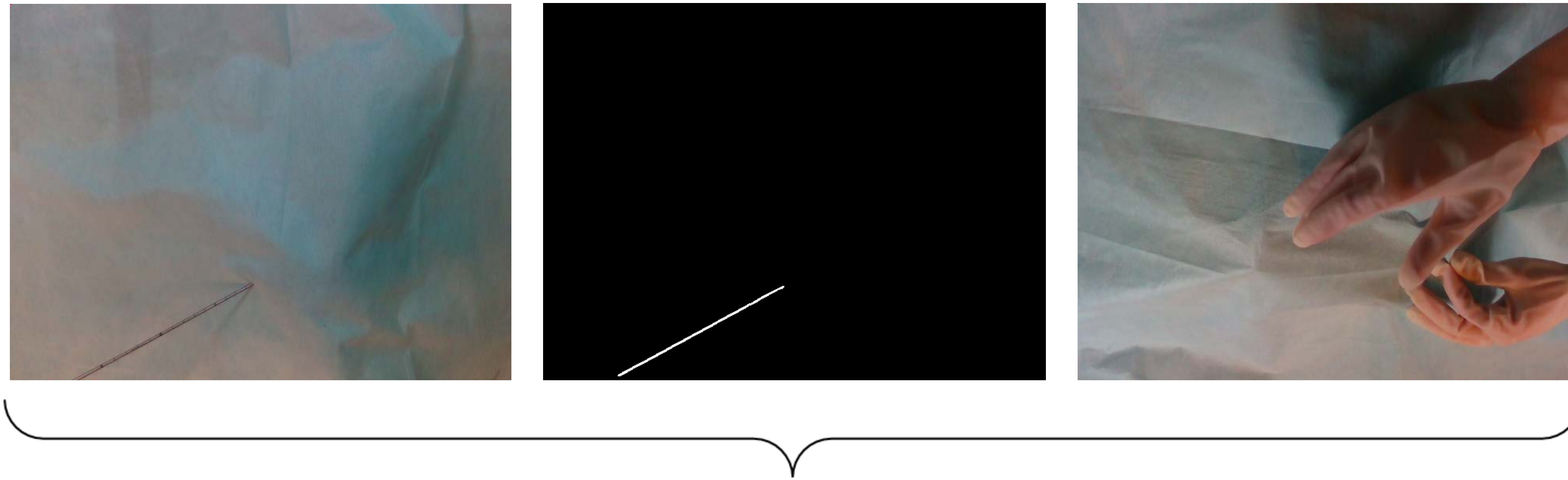
Varying Colour

Background images

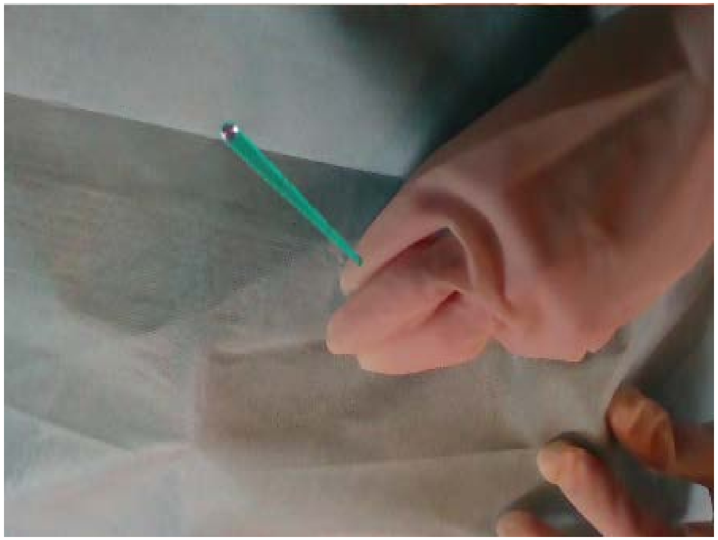


Increasing Complexity

Data Set Creation – Composing Images



Data Set Creation – Challenges

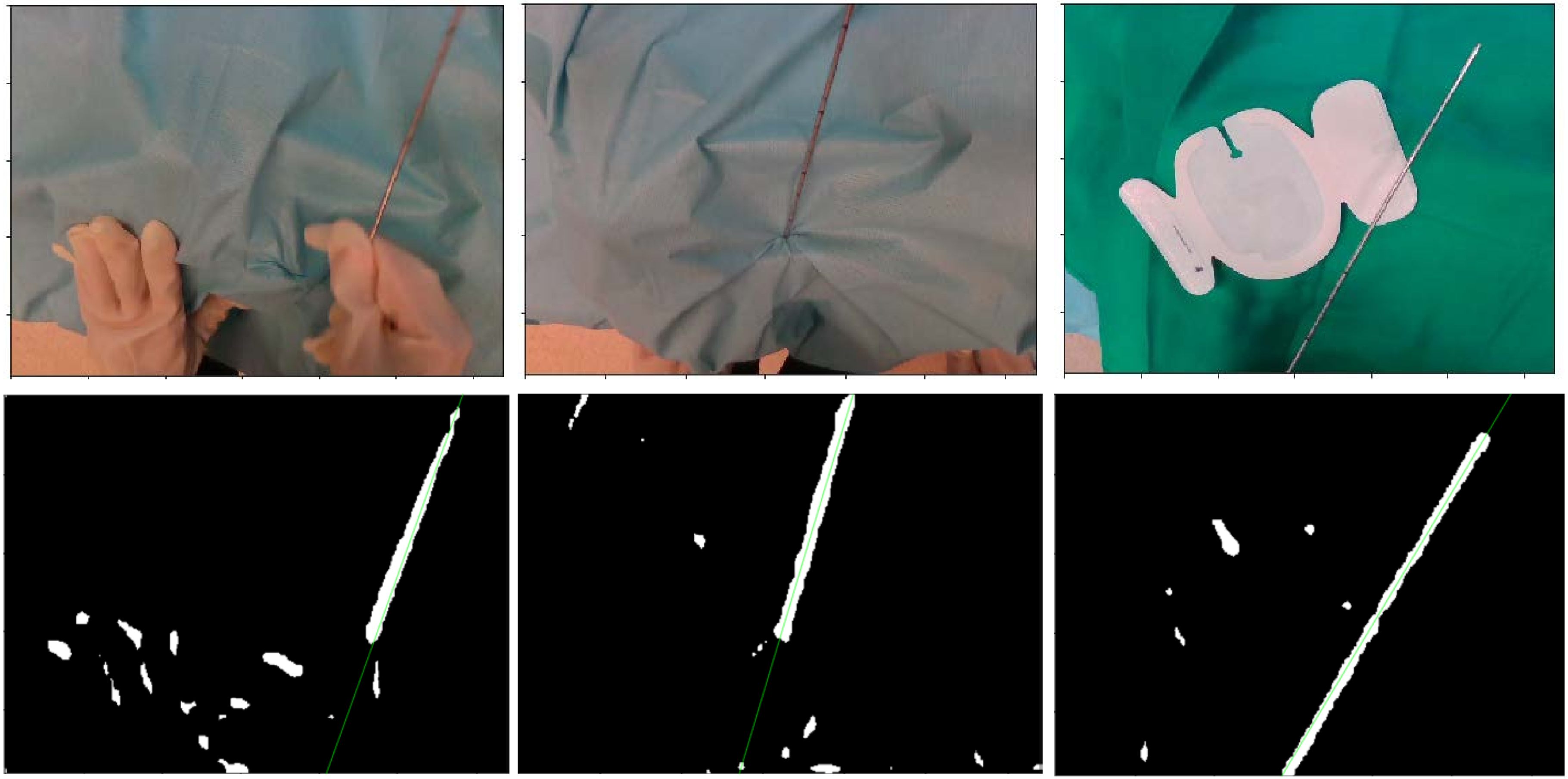


No colour blending

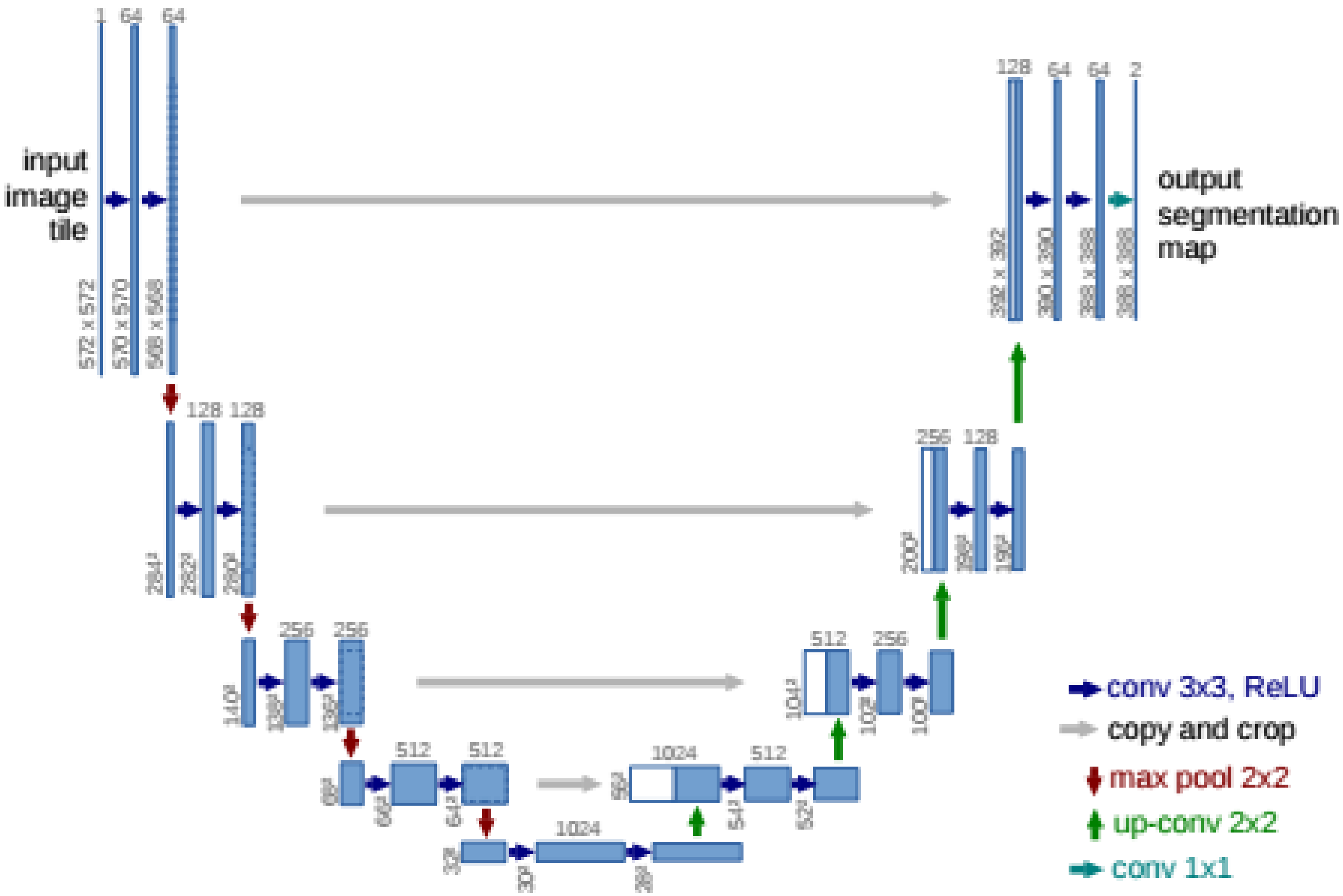
Too perfect colour blending

- Histogram matching in each LAB channels
- Outward Gaussian blurring on the mask to smooth edges

Technical Approach – Holistically-Nested Edge Detection



U-Net



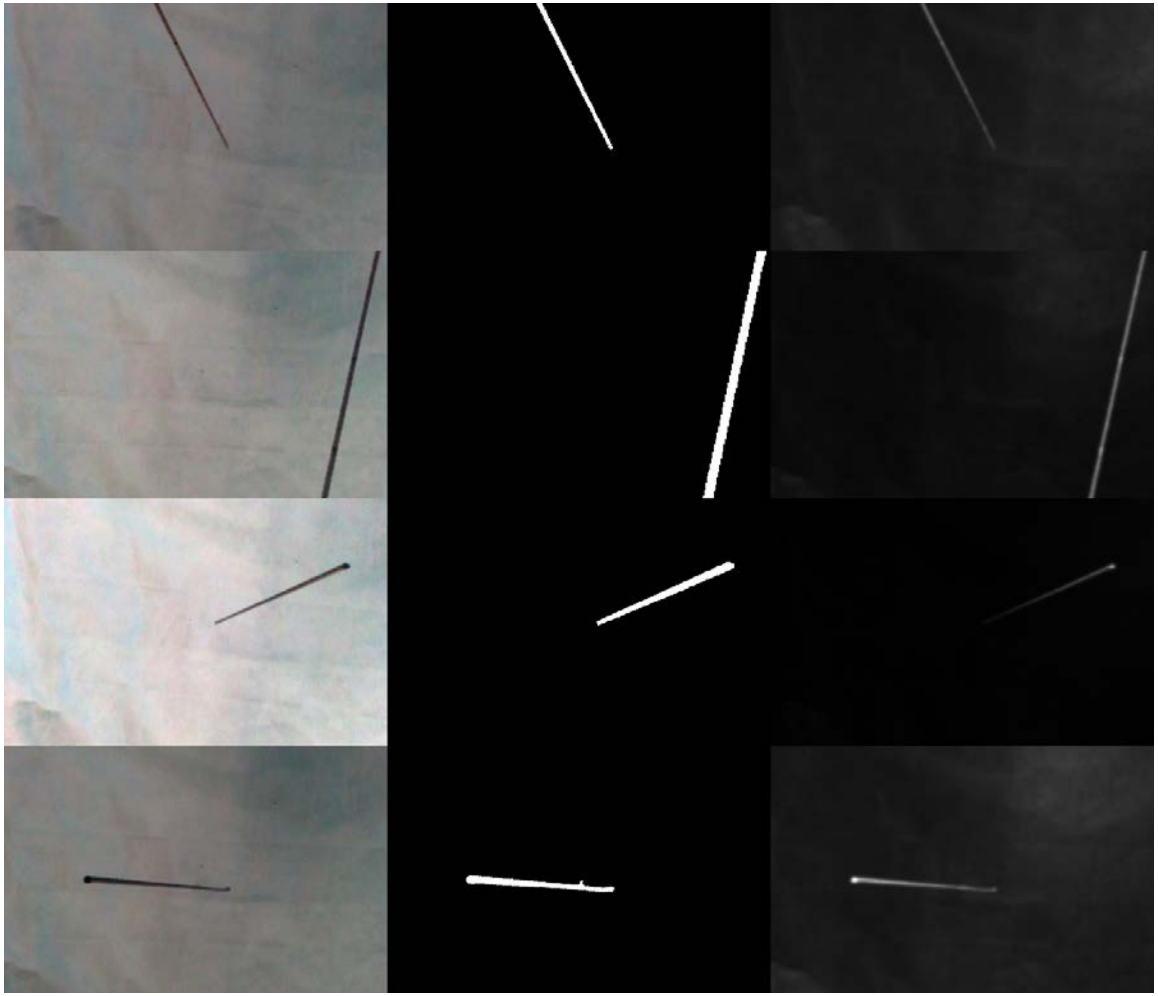
Fully convolutional network: retains semantic context, better for memory usage

[9] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation

U-Net

- Fully connected layers replaced by convolutional layers
- Usual contracting network supplemented by upsampling layers: increase the resolution of the output.
- High resolution features from contracting path combined with upsampled output: retains image context
- Originally used with ~30 images! (with extensive augmentation)

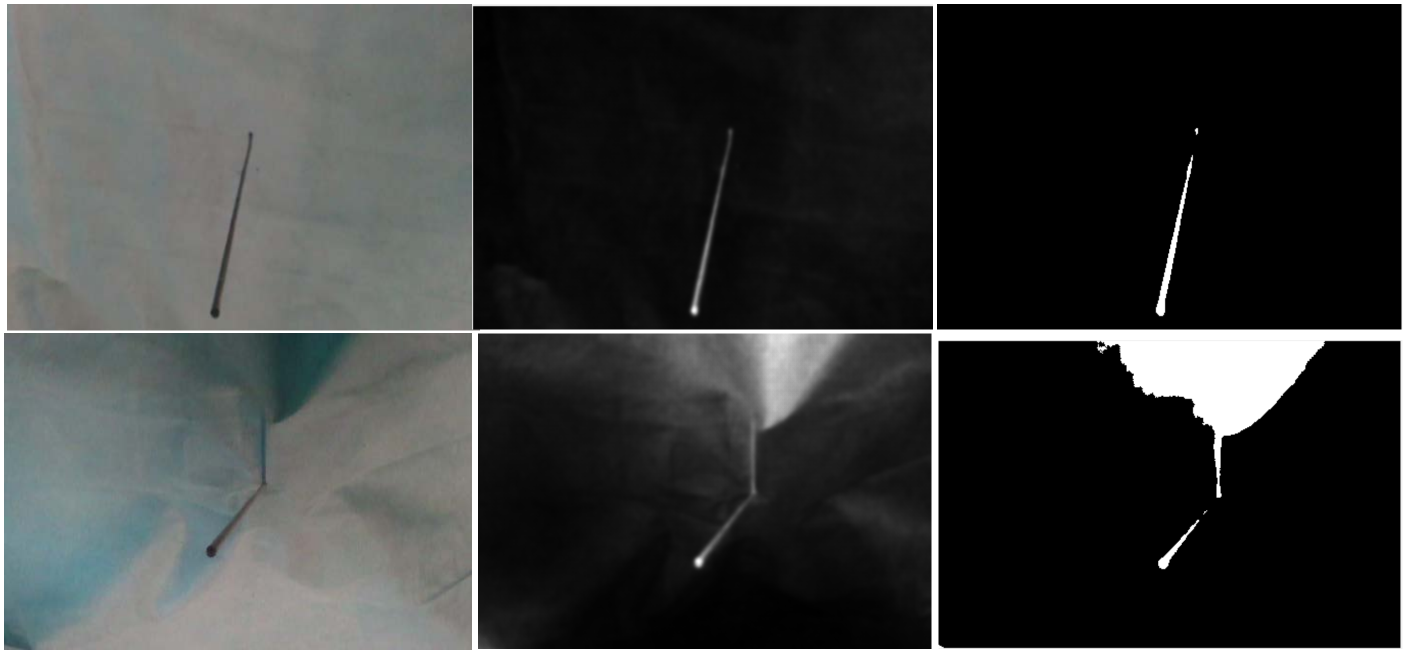
U-Net: Training with Level 1 Images



a) Original images   b) Ground truth c) Predictions

- 5 Layers
- Cross entropy loss with weight balancing
- Adam optimizer

U-Net: Challenges



Disjoint masks
(Train for longer)

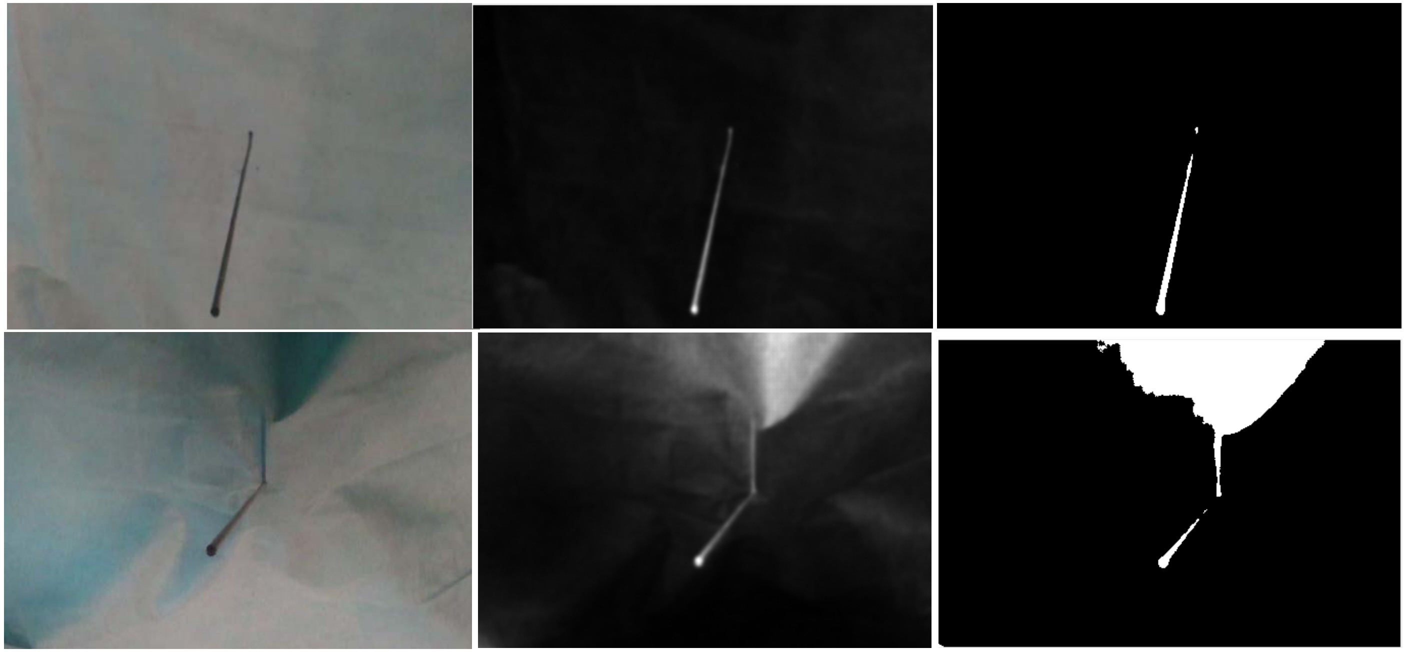
Low quality masks

a) Original image b) Prediction c) After post-processing

Possible solutions:

- Experiment with hyper-parameters etc
- Train using higher level images directly
- Better post-processing

U-Net: Challenges



Disjoint masks (train for longer)

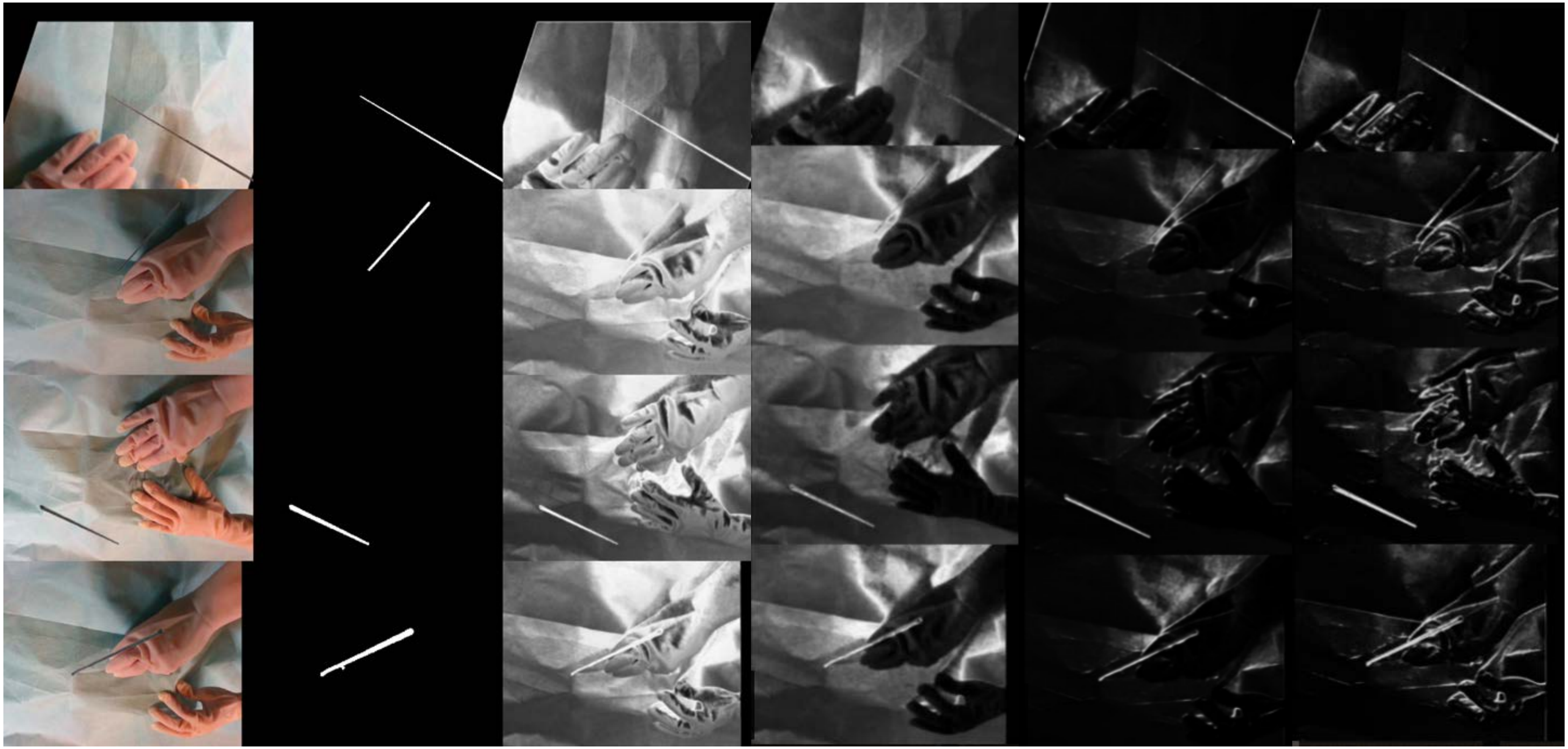
Low quality masks

a) Original image b) Prediction c) After post-processing

Possible solutions:

- Experiment with hyper-parameters etc
- **Train using higher level images directly**
- Better post-processing

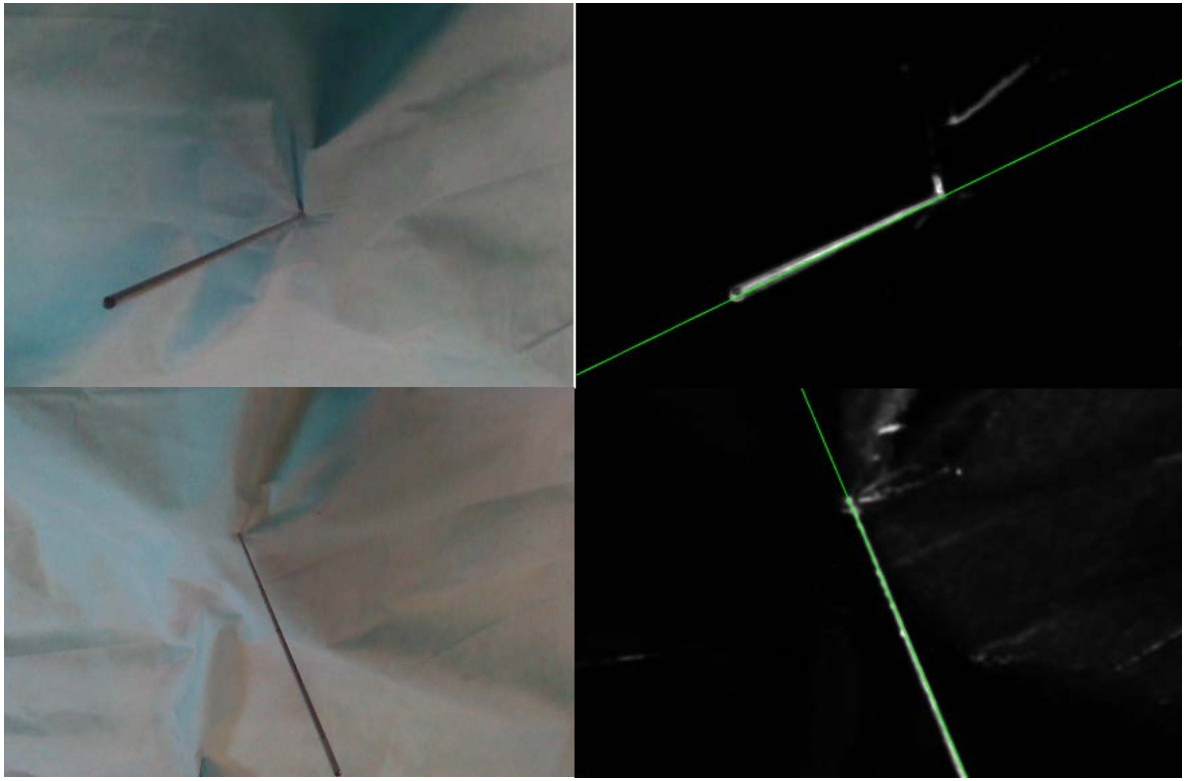
U-Net- Retrain with Level 2 Images



Original Ground truth Epoch 1 Epoch 25 Epoch 115 Epoch 200

U-Net: Retrain with Level 2 images

Results



a) Original image b) Prediction

Much better results on Level 1 images!

- Refine network
- Post-processing

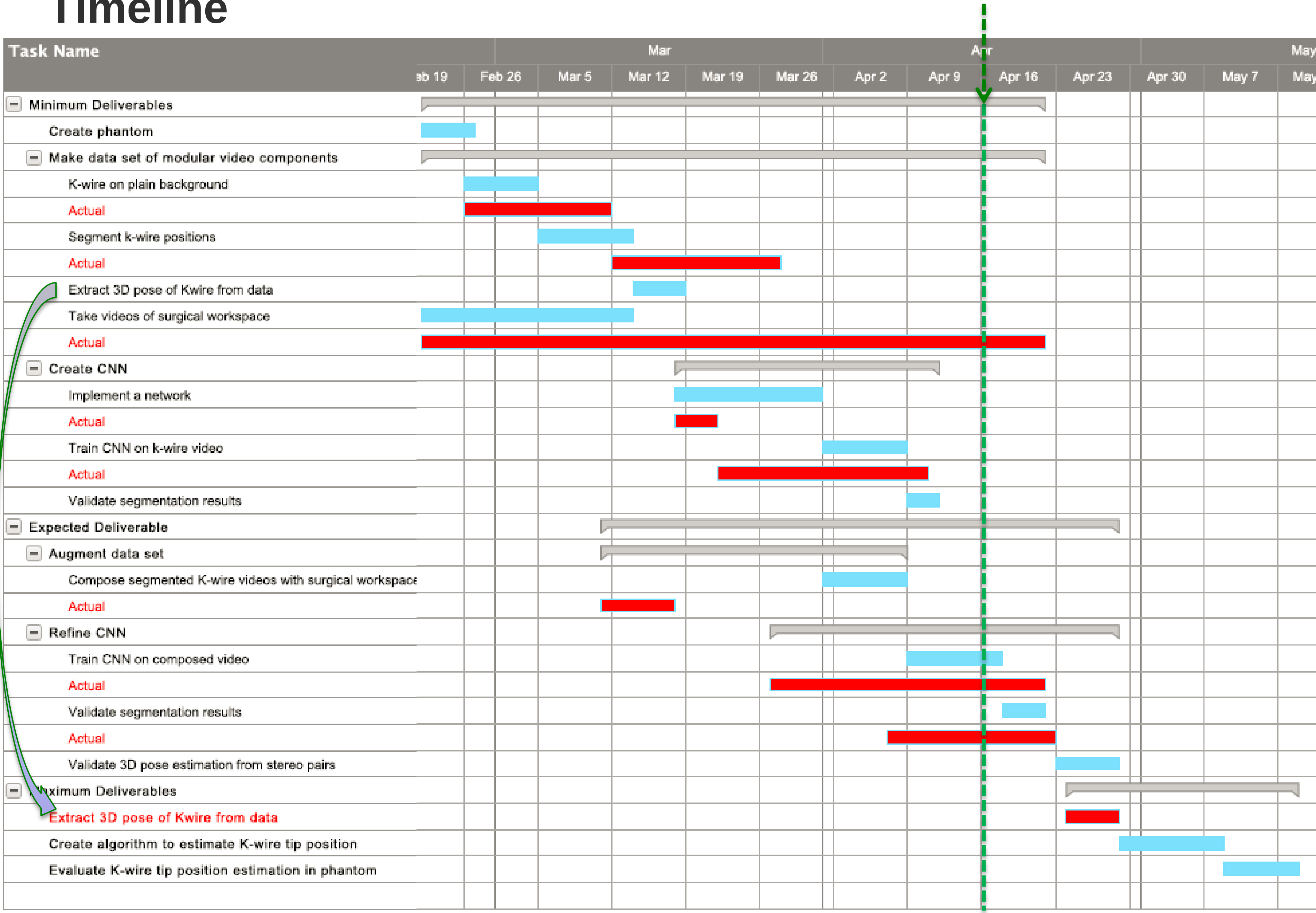
U-Net: Further

- Refine network to increase accuracy
  - Iterative!
  - Better post-processing methods
- Validation with new data
- Orientation estimation in 3D

Dependencies

Dependency	Status	Plan
Access to servers for training CNN	✓	
~~Get Keras installed in server~~	~~In progress~~	~~Contacted Anton~~
Access to camera and surgical instruments	✓	
Access to segmentation library	✓	
Create a phantom	✓	
Observe K-wire use in clinic	In progress	In discussion with Alex Johnson
Usage limit on thin6 server	In progress	Obtained access to MARCC cluster, run on desktop with GPU

Timeline


Task Name
Mar
Apr
May
eb 19
Feb 26
Mar 5
Mar 12
Mar 19
Mar 26
Apr 2
Apr 9
Apr 16
Apr 23
Apr 30
May 7
May
Minimum Deliverables
Create phantom
Make data set of modular video components
K-wire on plain background
Actual
Segment k-wire positions
Actual
Extract 3D pose of Kwire from data
Take videos of surgical workspace
Actual
Create CNN
Implement a network
Actual
Train CNN on k-wire video
Actual
Validate segmentation results
Expected Deliverable
Augment data set
Compose segmented K-wire videos with surgical workspace
Actual
Refine CNN
Train CNN on composed video
Actual
Validate segmentation results
Actual
Validate 3D pose estimation from stereo pairs
Maximum Deliverables
Extract 3D pose of Kwire from data
Create algorithm to estimate K-wire tip position
Evaluate K-wire tip position estimation in phantom

Reading List

1. Fischer, Marius, et al. "Preclinical usability study of multiple augmented reality concepts for K-wire placement." International Journal of Computer Assisted Radiology and Surgery 11.6 (2016): 1007-1014.
2. Jégou, S., Drozdzal, M., Vazquez, D., Romero, A., & Bengio, Y. (2016). The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation. *arVix Preprint*. Retrieved from http://arxiv.org/abs/1611.09326
3. Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015.
4. Pakhmov et. al, Semantic-boundary-driven approach to Instrument Segmentation for Robotic Surgery
5. Lee et. al, Simultaneous Segmentation, Reconstruction and Tracking of Surgical Tools in Computer Assisted Orthopedics Surgery
6. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In Medical Image Computing and Computer Assisted Intervention - MICCAI 2015 (Vol. 9351, pp. 234–241). Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28
7. Szegedy, C., Reed, S., Erhan, D., Anguelov, D., & Ioffe, S. (2014). Scalable, High-Quality Object Detection. arXiv. Retrieved from http://arxiv.org/abs/1412.1441