# K-wire Tracking in 3D Camera Views

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## Introduction

K-wire is a commonly used tool in many orthopedic surgeries. The goal of this project is to provide K-wire detection and tracking to aid insertion.

Currently K-wire insertion:
1. Is time consuming
2. Requires many X-rays
3. Could require multiple attempts
4. Could damage important structures

## Problem Statement

We propose a deep learning based K-wire tracking algorithm using RGB images. This eliminates the need for multiple X-ray images. In addition such a technique can be easily integrated into augmented reality solutions for orthopedics surgery.

## Solution

1. Data Creation:
- Capture the K-wire and scene separately
- Augment K-wire and scene separately
- Compose them in stages to vary complexity

Fig: Varying data complexity: a) Level 0 b) Level 1 c) Level 2

2. Network Architecture:
- Train the network on incrementally more complex data
- Explore two different kinds of networks: U-Net and HED
- Both fully convolutional networks that allow end to end training and give pixel wise segmentation masks

3. Validation:
- 2D validation: compare orientations of the K-wire in images
- 3D validation: Triangulate 2D orientations into 3D using the stereo parameters
- Ground truth: manual segmentation on ~40 images (~40)

## Management Summary

- Met a few times per week to discuss progress, issues, next steps and work distribution
- Athira: Image augmentation, U-Net
- Jie Ying: Data composition, HED
- Both: Data collection, Validation
- Weekly meetings with mentors

## Acknowledgements

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## Results

We validate the networks on natural (not composed) images. Both U-Net and HED perform reasonably well with Level 0 and Level 1 images. Level 2 images throw some difficulties to both the networks, due to the presence of similar instruments like scissors.

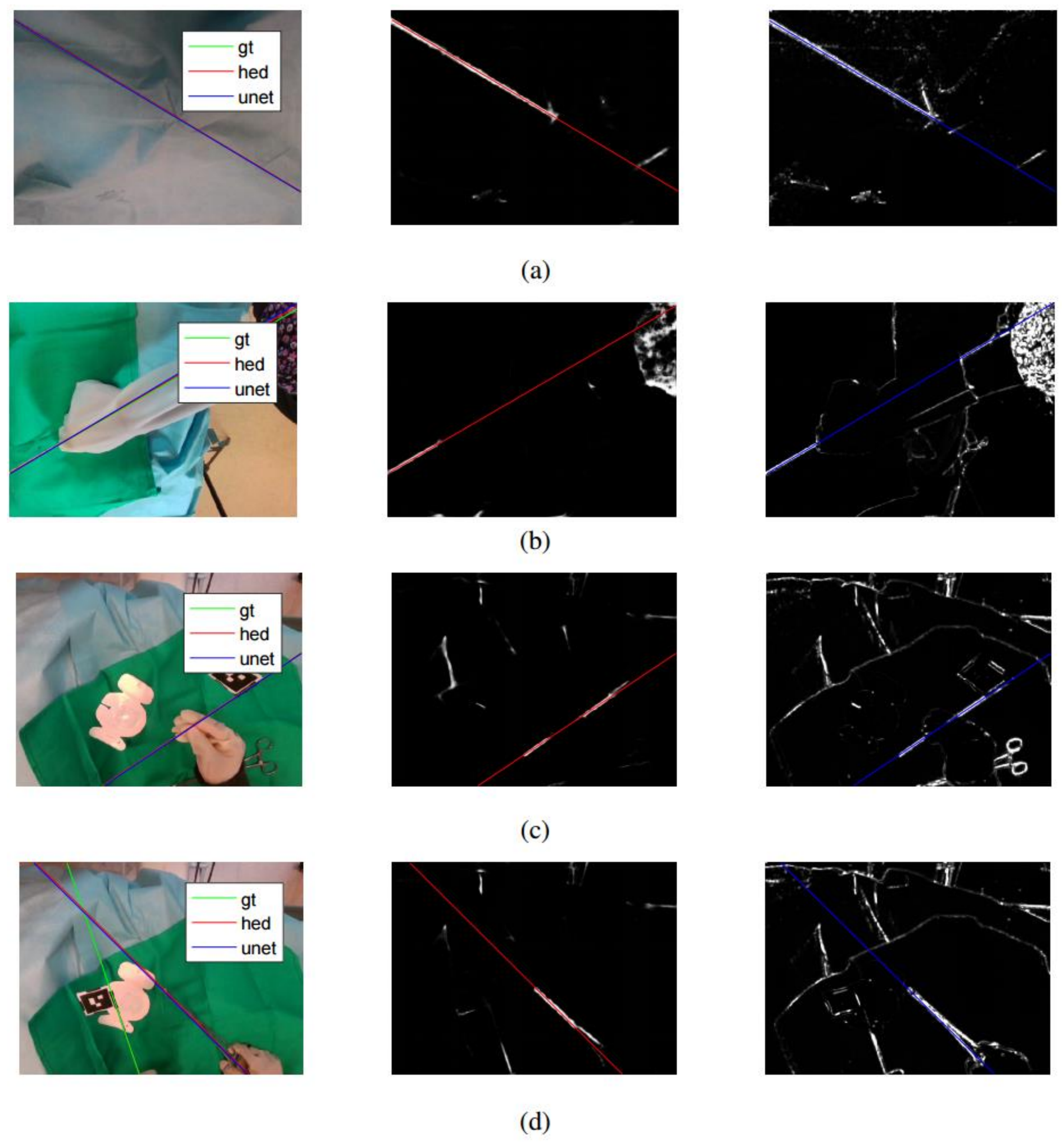


Fig: Original images, centre: HED output, right: U-Net output. These figures show sample successes and failures from Level 0 (a), Level 1 (b) and Level 2 (c & d) images

**Table 1: Success Rate and Error in 2D**

| Level | No. of Images | Correct Detections | | Error (deg) | | | |
|---|---|---|---|---|---|---|---|
| | | HED | U-Net | HED | | U-Net | |
| | | | | Mean | Var. | Mean | Var. |
| 0 | 10 | 10 | 10 | 0.33 | 0.25 | 0.40 | 0.27 |
| 1 | 10 | 10 | 10 | 0.55 | 1.00 | 0.50 | 0.37 |
| 2 | 10 | 18 | 13 | 0.83 | 1.43 | 0.77 | 1.19 |

**Table 2: Success Rate and Error in 3D for Individual Stereo Pairs**

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HED | Success | T | T | T | T | T | F | T | F | T | T | Mean | Var. |
| | Err (°) | 1.5 | 3.2 | 20.1 | 0.6 | 1.0 | - | 1.1 | - | 4.2 | 0.2 | 4.0 | 44.5 |
| U-Net | Success | T | F | F | T | F | F | T | T | F | F | Mean | Var. |
| | Err (°) | 16.4 | - | - | 1.2 | - | - | 2 | 4.6 | - | - | 6.0 | 49.9 |

## Discussion

- Composed images can be used to augment datasets that generalize to natural images
- HED shows better performance than the U-Net though that could be because of starting with pre-trained weights
- Common point of failure is when the network detects scissors
- 2D errors could get magnified greatly in 3D

## Future Work

- Improve K-wire detection in the presence of other tools
- Searching for the K-wire in the corresponding region of the other image, when it is detected only in one
- Identifying pose in 3D

## Lessons Learned

- Software experience in TensorFlow
- Deep learning knowledge: Fully convolutional neural networks, effects of hyperparameter tuning
- The importance of various techniques learned in other classes such as stereo camera calibration, transformations between camera spaces, tool space, and AR toolkit marker space, and Epipolar geometry