**Tool Tracking in Orthopedics Surgery**
**600.646 Computer Integrated Surgery II, Spring 2017**

**Project Proposal**

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**Summary and goals:**

K-wire tracking is an important part of computer assisted orthopedics surgery. Currently, multiple intra-operative X-ray images are taken while inserting a K-wire, resulting in high radiation exposure for the physician. We propose a deep learning based K-wire tracking algorithm using RGBD images, that eliminates the need for multiple X-ray images and can be easily integrated into augmented reality solutions to orthopedics surgery.

**Background:**

Kirshner wires or K-wires are long, smooth stainless steel pins that are widely used in orthopedics surgery to hold bones together. The pins are driven through the skin using a power or hand drill. They can be used for temporary fixation before inserting screws or permanent fixation while the bones heal. K-wire and screw insertion is currently done with minimally invasive techniques, involving modern imaging technology and computer aided navigation systems. Correct placement requires numerous intra-operative X-ray images, and often requires multiple attempts before the surgeon achieves satisfactory placement and orientation [1]. Misplacement of the K-wire could cause severe damage to external iliac artery and vein, obturator nerve and other structures [2]. This leads to multiple entry wounds on the patient, high X-ray exposure for the patient and the surgical staff, increased OR time and frustration of the surgical team. A single K-wire insertion could take as much as 10 minutes [3].

The main challenge during K-wire insertion has been identified as the mental alignment of patient, medical instruments and intra-operative X-rays [4]. Recently, camera augmented solutions have been proposed to help surgeons in this mental alignment [5,6]. Multi-modal fusion between 3D surface from RGBD cameras and digitally reconstructed radiographs have been shown to considerably reduce the duration of surgeries, the number of X-rays, overall radiation dose and the surgical workload [7].

**Motivation:**

Any computer assisted solution to assist surgeons in the mental alignment and localization, including augmented reality based solutions, will eventually require tracking of the K-wire. Conventional navigation systems for tool tracking are mainly based on tracking of optical markers and recovering the spatial transformation between the patient, medical images and the tool. Though such navigation systems offer sub-millimeter accuracy [8] , they cannot be extended to K-wires. Although we can attach an optical tracker to the drill, the K-wire can slide in and out of the drill, preventing accurate calibration. K-wires are also too thin to be tracked by depth camera and too shiny to be segmented from RGB using traditional computer vision techniques. Thus, we will explore deep learning tools to learn more structurally-based features.

**Technical Approach:**

We propose a real time tracking of the K-wire using on RGB data. Traditional computer vision methods face challenges in this task due to non-uniform lighting, occlusions, and the complex background. Hence deep learning is used to segment the surgical video.

The solution can be divided into three main parts:

1. **Data creation**

Large, quality data is essential to training a successful neural network. Since there is no data set available for K-wire tracking, our first step is to create one. We will capture the foreground (K-wire) and background (scene including drape, instruments etc.) separately and compose them in stages to generate data of varying complexity. By capturing the foreground separately on a plain background (Figure 1 a) Sample foreground shot before segmentation (left), we can easily segment the K-wire to obtain soft ground truth for position. We propose to train the network on the simplest data and increment the complexity of the data once we have a basic trained network that can distinguish the K-wire against a plain background. The final step would be to compose a dataset using actual videos from a surgery.

**Figure 1 a) Sample foreground shot before segmentation (left). Sample background images (middle and right)**

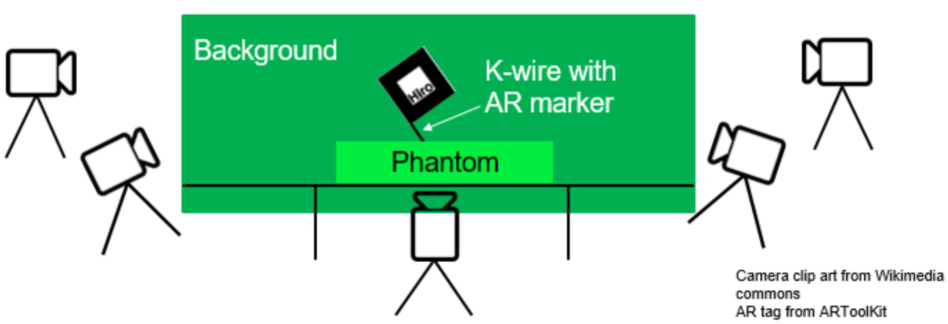



**Figure 2) Proposed scene setup with 5 calibrated cameras around the K-wire, which is inserted into the phantom**

## 2. Network architecture

A few potential network architectures have been identified.

a. Holistically-nested Edge Detection) for tool segmentation [10]

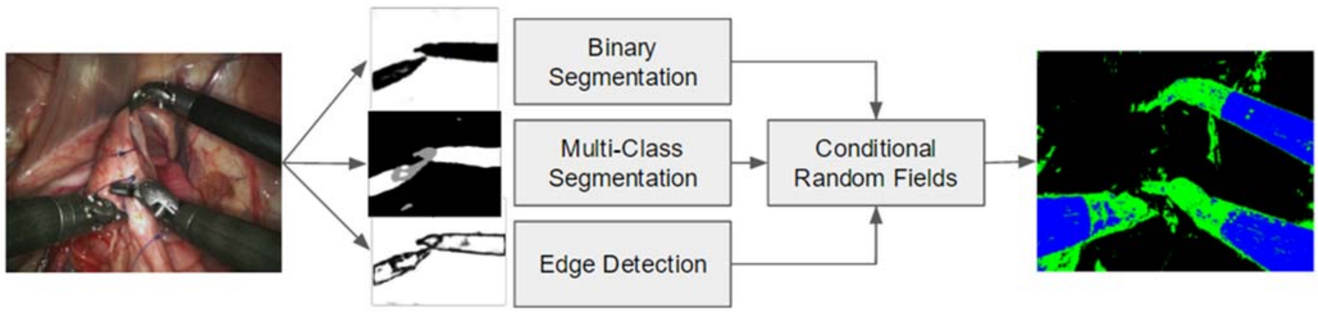



Figure 3) Schematic of the network architecture

This approach uses three fully convolutional networks (FCN's) to simultaneously perform 2D multi-class segmentation, binary segmentation and edge detection. Finally Conditional Random Fields are used to refine the mask from the multi-class using outputs from binary segmentation and edge detection.

b. U-Nets [11]

U-Nets have been shown to give good results in biomedical image segmentation. These networks rely on fully convolutional layers to combine features at different resolutions to achieve precise segmentations that retain semantic information. In addition, extensive data augmentation allows use of fewer training samples.

## 3. Pose estimation

We will use epipolar geometry to do pose estimation from stereo images. 2D segmentations from the RGB images can be used to know the 3D position of the K-wire with respect to the stereo camera. The cameras will be pre-calibrated with a checkerboard pattern. In capturing our data, we will use an AR tag on the K-wire to create ground truth location for it. The AR tag will then be removed, prior to taking the video.

In our validation dataset, with X-ray and RGBD camera, as in the CamC[12] set up, we will calibrate the two with metal lined checkerboard pattern. The orientation of the K-wire is thus obtained by extending the line to infinity. The final step (maximum deliverable) would be to identify the tip of the K-wire on this infinite line, which could be potentially done by identifying markings on the K-wire.

**Deliverables:**

- **Minimum:**
  - Phantom to create training data
  - Modular data set
    - Foreground videos with K-wire against green drape
    - Segmentations of the K-wire position
  - CNN trained on K-wire video with plain background to segment position

- **Expected:**
  - Realistic data set of surgical workspace by composing foreground and background videos of surgical workspace with instruments (ie. scalpel)
  - CNN trained with realistic data that can segment K-wire
  - Algorithm to extract K-wire orientation from segmented position
- **Maximum:**
  - Algorithm to estimate position of K-wire tip inside the patient

**Management Plan:**

- Weekly CAMP meetings at 3pm Tuesday
- Group meeting: 2h on Tuesday and Friday
- Meeting with different mentors for each part as needed
- Code management by Git

| Jie Ying | Athira |
|---|---|
| Set up phantom and scene | Do camera calibration |
| Collect data | |
| Preprocess data | |
| Implement one network | Implement one network |
| Analyze and compare results of each net | |
| Compose videos | Extract 3D pose information |
| Create algorithm to estimate tip position | |

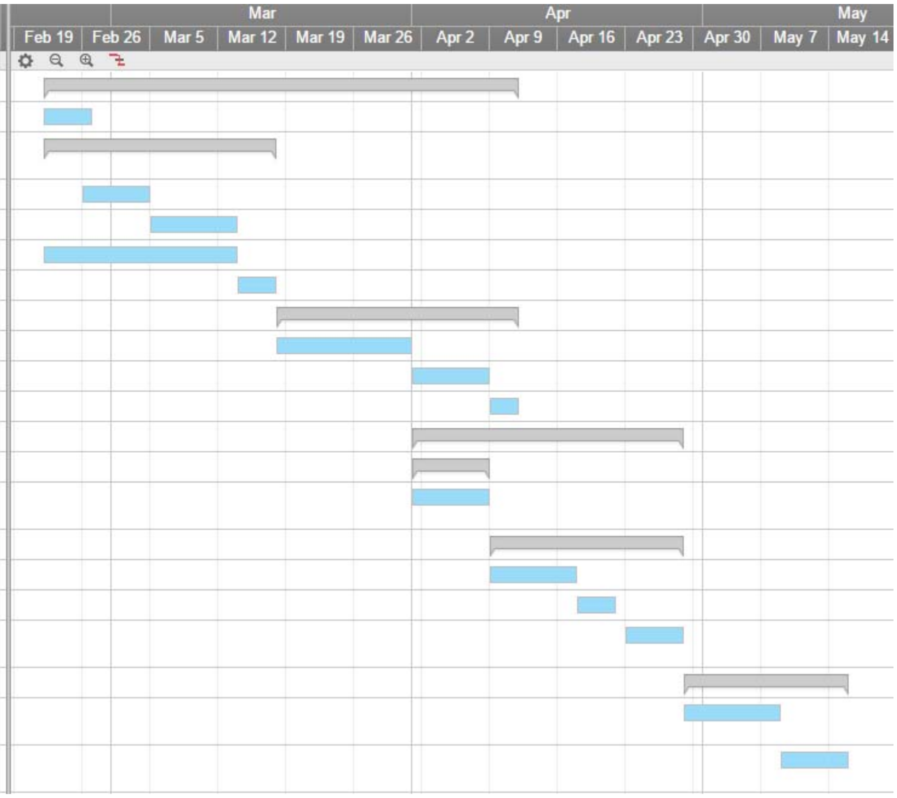
**Figure 4 Work division**

**Dependencies:**

| No. | Dependency | Status | Plan | |
|---|---|---|---|---|
| 1 | Access to servers for training CNN | Resolved | | |
| 2 | Get Keras installed in server | In progress | Resolve by Feb $28^{th}$ | Contacted Anton |
| 3 | Access to camera and surgical instruments | Resolved | | |
| 4 | Access to segmentation library | Resolved | | |
| 5 | Learn to create a phantom | Unresolved | Resolve by Feb $28^{th}$ | Discuss with Javad |
| 6 | Observe K-wire use in clinic | In progress | First visit, no K-wire used | Planned future visits to the OR |

**Timeline:**

| Task Name | Start | Finish | Duration |
|---|---|---|---|
| **Minimum Deliverables** | 02/22/17 | 04/11/17 | 49d |
| **Create phantom** | 02/22/17 | 02/26/17 | 5d |
| **Make data set of modular video components** | 02/22/17 | 03/17/17 | 24d |
| K-wire on plain background | 02/26/17 | 03/04/17 | 7d |
| Segment k-wire positions | 03/05/17 | 03/13/17 | 9d |
| Take videos of surgical workspace | 02/22/17 | 03/13/17 | 20d |
| Extract 3D pose | 03/14/17 | 03/17/17 | 4d |
| **Create CNN** | 03/18/17 | 04/11/17 | 25d |
| Implement a network | 03/18/17 | 03/31/17 | 14d |
| Train CNN on k-wire video | 04/01/17 | 04/08/17 | 8d |
| Validate segmentation results | 04/09/17 | 04/11/17 | 3d |
| **Expected Deliverable** | 04/01/17 | 04/28/17 | 28d |
| **Augment data set** | 04/01/17 | 04/08/17 | 8d |
| Compose segmented K-wire videos with surgical workspace | 04/01/17 | 04/08/17 | 8d |
| **Refine CNN** | 04/09/17 | 04/28/17 | 20d |
| Train CNN on composed video | 04/09/17 | 04/17/17 | 9d |
| Validate segmentation results | 04/18/17 | 04/21/17 | 4d |
| Validate 3D pose estimation from stereo pairs | 04/23/17 | 04/28/17 | 6d |
| **Maximum Deliverables** | 04/29/17 | 05/15/17 | 17d |
| **Create algorithm to estimate K-wire tip position** | 04/29/17 | 05/08/17 | 10d |
| **Evaluate K-wire tip position estimation in phantom** | 05/09/17 | 05/15/17 | 7d |




**Reading list:**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[10] Pakhmov et. al, Semantic-boundary-driven approach to Instrument Segmentation for Robotic Surgery

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