# K-Wire Tracking in 3D Camera Views

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# **Recap: 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.

**Recap: Workflow** 







Advanced Computer-Integrated Surgery

## I. Pre-clinical usability study (CAMP, JHU; I JCARS 2016)

Int J CARS (2016) 11:1007–1014 DOI 10.1007/s11548-016-1363-x	CrossMark				
ORIGINAL ARTICLE					
Preclinical usability study of multiple augmented reality concepts for K-wire placement					
$\begin{array}{l} Marius \ Fischer^{1,2} \ \cdot \ Bernhard \ Fuerst^{2,3} \textcircled{0} \ \cdot \ Sing \ Chun \ Lee^2 \ \cdot \ Javad \ Fotouhi^2 \ \cdot \ Severine \ Habert^3 \ \cdot \ Simon \ Weidert^1 \ \cdot \ Ekkehard \ Euler^1 \ \cdot \ Greg \ Osgood^4 \ \cdot \ Nassir \ Navab^{2,3} \end{array}$					
Received: 29 January 2016 / Accepted: 24 February 2016 / Published online: 19 March 2016 © CARS 2016					
Abstract <i>Purpose</i> In many orthopedic surgeries, there is a demand	augmentation on 2D video, and 3D surface reconstruction augmented by digitally reconstructed radiographs and live				

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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.

### Introduction

- K-wire placement: widely prevalent and challenging minimally invasive technique
- Main challenge: Mental alignment of patient, medical instruments, and the intra-operative X-ray images
- K-wire insertion currently requires many X-rays
  - Misplacement could damage important structures in the body
  - Multiple entry wounds
  - High radiation exposure



#### **Experiments:**

- Phantom design:
  - Thin, tubular mesh made out of aluminium, enclosed in methylene bisphenyl diisocyanate (MDI) foam, which is stiff, lightweight, and not radiopaque
  - Begin and end of the bone were marked with a rubber radiopaque ring
  - Similar haptic feedback
- 7 surgeons, each performed three K-wire placements



Imaging systems compared:

- a) Conventional intra-operative X-ray imaging
- b) 2D RGB video and X-ray visualization
- c) 3D RGBD and DRR via CBCT visualization





#### Imaging systems compared:

- a) Conventional intra-operative X-ray imaging
  - Baseline
  - Operated in digital radiography mode

b) 2D RGB video and X-ray visualization

c) 3D RGBD and DRR via CBCT visualization





#### Imaging systems compared:

a) Conventional intra-operative X-ray imaging

b) 2D RGB video and X-ray visualization

- X-ray augmented onto 2D camera view
- X-ray camera calibration with a single plane phantom with radiopaque markers
- Requires repositioning of the C-arm to change the optical and X-ray view

c) 3D RGBD and DRR via CBCT visualization





#### Imaging systems compared:

a) Conventional intra-operative X-ray imaging

b) 2D RGB video and X-ray visualization

- c) 3D RGBD and DRR via CBCT visualization
  - Augmentation of digitally reconstructed radiographs from cone beam CT onto patient surface from RGBD camera
  - Allows simultaneous visualization from multiple, arbitrary views
  - CBCT-RGBD calibration through surface matching





**Evaluation metrics:** 

- 1. Duration of each K-wire placement
- 2. Number or X-ray images
- 3. Cumulative dose
- 4. Error in placement
  - Average distance from the center line of bone phantom
- 5. Surgical task load
  - Surgical Task Load Index questionnaire (SURG-TLX)



### **Results**



- Rigorous statistical testing was performed to prove significance
- RGBD/ DRR gives significant improvements in all metrics except accuracy



### Conclusions

- 3D visualization yields the most benefit in terms of surgical duration, number of X-ray images taken, overall radiation dose, and surgical workload
- Movement of the C-arm or surgical table may lead to loss of tracking, which results in an outdated mixed reality visualization
- Mixed reality visualizations currently do not provide an augmentation of a tracked tool: this could give more pronounced improvements



**II. U-Net** (University of Freiburg, MICCAI 2015)

#### U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, and Thomas Brox

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Abstract. There is large consent that successful training of deep networks requires many thousand annotated training samples. In this paper, we present a network and training strategy that relies on the strong use of data augmentation to use the available annotated samples more efficiently. The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. We show that such a network can be trained and to and from your

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer International Publishing, 2015.

V] 18 May 2015

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### Background

Traditionally segmentation done in a 'patch' based manner

- Gives pixel wise labelling
- Slow
- Trade-off between context and localization accuracy

Fully convolutional networks (FCN):

- Fully connected layers replaced by convolutional layers and add upsampling layers
- End to end training
- Retains spatial information



### **Network architecture**



### **Features**

- Extensive data augmentation
  - ~30 training images
  - Random elastic deformations



- Balance different classes
- Assign high weights to separating background pixels

$$w(\mathbf{x}) = w_c(\mathbf{x}) + w_0 \exp\left(-\frac{(d_1(\mathbf{x}) + d_2(\mathbf{x}))^2}{2\sigma^2}\right)$$

- *wc* :  $\Omega \rightarrow R$ : weight map to balance the class frequencies,
- $d1: \Omega \rightarrow R$ : distance to the border of the nearest cell
- $d2: \Omega \rightarrow R$ : distance to the border of the second nearest cell



Fig. Sample images a) DIC HeLa cells b) Ph3-U373 dataset

### Results

#### **ISBI cell tracking challenge 2015**



(a) part of an input image of the "PhC-U373" data set. (b) Segmentation result (cyan mask) with manual ground truth (yellow border) (c) input image of the "DIC-HeLa" data set. (d) Segmentation result (random colored masks) with manual ground truth (yellow border).

	Name	PhC-U373	DIC-HeLa
	IMCB-SG (2014)	0.2669	0.2935
Segmentation results (IOU) on the ISBI cell tracking challenge 2015	KTH-SE (2014)	0.7953	0.4607
	HOUS-US (2014)	0.5323	-
	second-best $2015$	0.83	0.46
	u-net $(2015)$	0.9203	0.7756



### Results

**ISBI EM segmentation challenge** 

Sample image and ground truth



Ranking on the EM segmentation challenge [14] (march 6th, 2015), sorted by warping error.

Rank	Group name	Warping Error	Rand Error	Pixel Error
	$^{\ast\ast}$ human values $^{\ast\ast}$	0.000005	0.0021	0.0010
1.	u-net	0.000353	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [2]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	0.0582
:				
10.	IDSIA-SCI	0.000653	0.0189	0.1027



**Computer Aided Medical Procedures**