



# CathNets: Detection and Single-View Depth Prediction of Catheter Electrodes

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## Overview and Motivation

- Electrophysiology procedures are commonly carried out under guidance of C-arm fluoroscopy, but precise localization of the surgical instruments within the patients anatomy is done using expensive electro-anatomic mapping systems
- **Potential Alternative:** Optical catheter detection, tracking & 3D reconstruction in fluoroscopic X-ray images
- **State of the Art:** i) Gaussian blob detectors<sup>[3,4]</sup> for detection, sparse coding for tracking<sup>[4]</sup> and graphical models<sup>[5]</sup> for 3D reconstruction
- **Contributions:** i) Fully automatic, robust & fast catheter electrode detection and ii) depth prediction from single-view X-ray images<sup>[6]</sup> using CNNs

## Methodology

### CathNet-Detect

- Fully Convolutional CNN<sup>[1]</sup> (FCN) for electrode detection
- Classifies each pixel into background, catheter tip or non-tip electrode

### Peculiarities

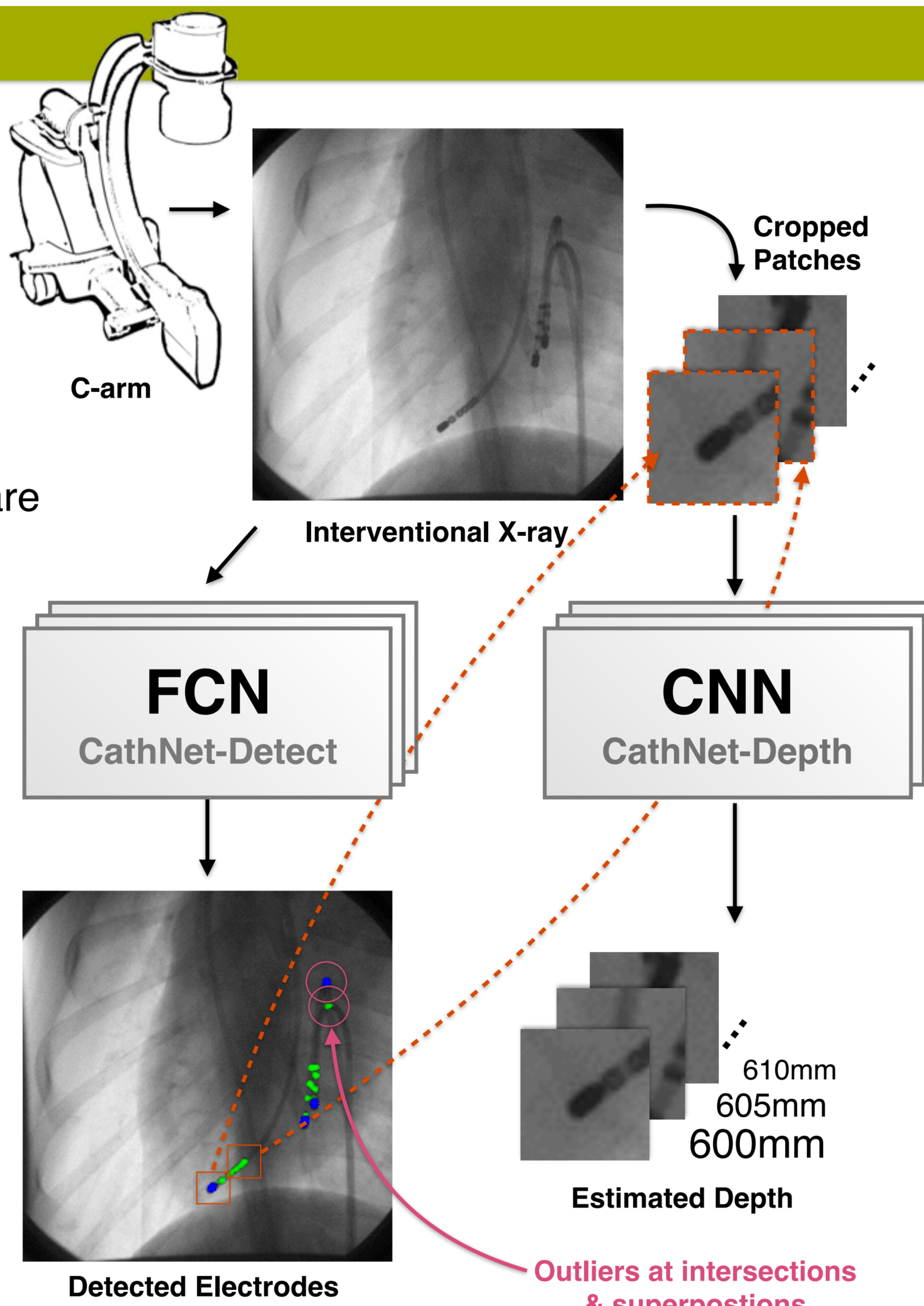
- Trained from large patches where electrode pixels are highly underrepresented
- We utilized a class balancing loss function to deal with the heavy class imbalance:

$$\mathcal{L}(\mathbf{x}_i, \mathbf{y}_i) = - \sum_j y_{ij} \cdot \log(\mathbf{x}_{ij}) \cdot \alpha_{\text{class}(i)}$$

↖ class probabilities of pixel i    ↖ weight of class i  
↖ ground-truth for pixel i

$$\alpha_{c_i} \cdot \frac{\sum_{px} \text{class}(px) == c_i}{n \cdot h \cdot w} = \frac{1}{|C|}$$

$$\Leftrightarrow \alpha_{c_i} = \frac{n \cdot h \cdot w}{|C| \cdot \sum_{px} \text{class}(px) == c_i}$$



### CathNet-Depth

- CNN for electrode depth prediction from single view X-ray images
- Regress depth w.r.t. the focal point of the C-arm

### Peculiarities

- Trained from small patches centered on electrodes
- Performed extensive training data augmentation because of an originally very small training dataset
- We utilized the Tukey loss which is robust to outliers<sup>[2]</sup>

## Dataset

**Dataset-A:** 20 pairs of co-registered and annotated monoplane X-ray images of a dog specimen from the LAT and PA view. Depth ground-truth was obtained via triangulation of electrodes in corresponding views.

**Dataset-B:** Additional 24 sequences (1650 frames) acquired during the same intervention

## Experiments & Results:

**CathNet-Detect:** We used Dataset-A for training (40 frames) and Dataset-B for testing (1650 frames). We trained both a model from full scale data and a down sampled version operating at half the resolution.

**CathNet-Depth:** From Dataset-A, 10 image pairs each were used for training & testing the depth regression model.

### CathNet-Detect: Detection Rate

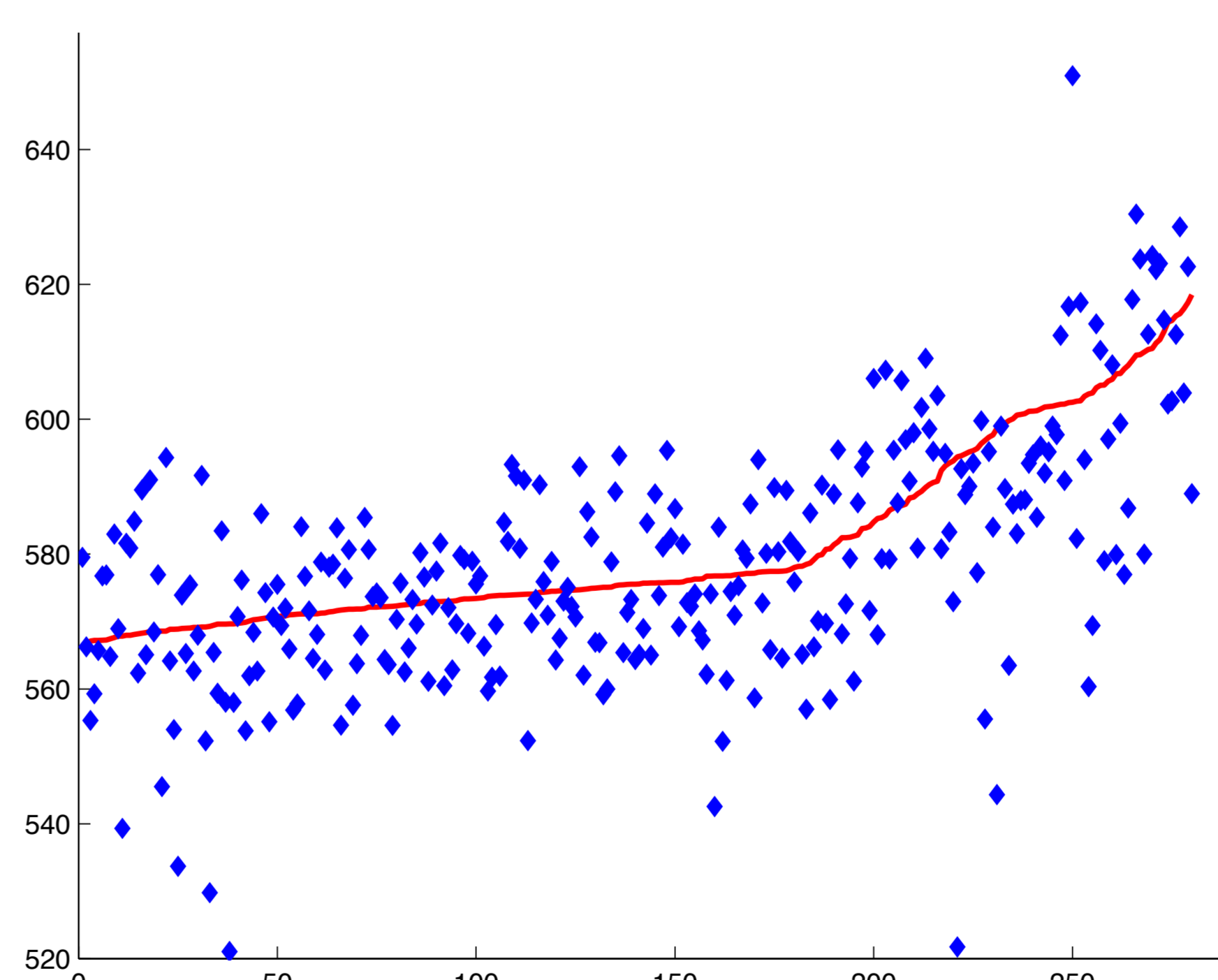
Method	All (PA)	Tips(PA)	All (LAT)	Tips (LAT)
Ours (Full Scale)	99.92%	99.92%	99.14%	100.0%
Ours (Half Scale)	99.77%	99.95%	99.49%	100.0%
Milletari et al. <sup>[4]</sup>	97.75%	-	95.77%	-

### CathNet-Detect: False Positive Rate

Model	All (PA)	Tips(PA)	All (LAT)	Tips (LAT)
Full Scale	0.210%	0.042%	0.120%	0.044%
Half Scale	0.360%	0.160%	0.570%	0.037%

### CathNet-Depth: Mean Absolute Error in [mm]

View	All	Tips	Non-Tips
PA	13.46 ± 11.50	14.11 ± 15.45	13.28 ± 10.25
LAT	8.24 ± 6.20	6.08 ± 4.66	8.83 ± 6.45
Combined	10.85 ± 9.59	10.01 ± 12.02	11.06 ± 8.83



Depth predictions for 280 testing electrodes, sorted by ground-truth depth in increasing order. The red line shows the ground-truth depth and blue diamonds the corresponding regression result.

## Conclusion:

- We presented a very robust and fully automatic catheter detector based on a FCN
- We showed promising results for depth prediction of catheter electrodes from single views
- Both could potentially be lined up for a 3D-reconstruction framework

## Future work:

- Use graphical models to map the detected electrodes to actual catheters
- Use geometrics constraint for depth estimation
- Working on low dose interventional X-ray images

## References:

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- [3] YingLiang Ma, Nicolas Coggin, Pascal Cathier, R James Housden, Geert Gijbbers, Michael Cooklin, Mark O'Neill, Jaswinder Gill, C Aldo Rinaldi, Reza Razavi, et al. Real-time x-ray fluoroscopy-based catheter detection and tracking for cardiac electrophysiology interventions. Medical physics, 40(7):071902, 2013.
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- [6] Shadi Albarqouni, Ulrich Konrad, Lichao Wang, Nassir Navab, and Stefanie Demirci. Single-view x-ray depth recovery: toward a novel concept for image-guided interventions. International Journal of Computer Assisted Radiology and Surgery, pages 1–8, 2016.

