



# Single-View X-ray Depth Recovery

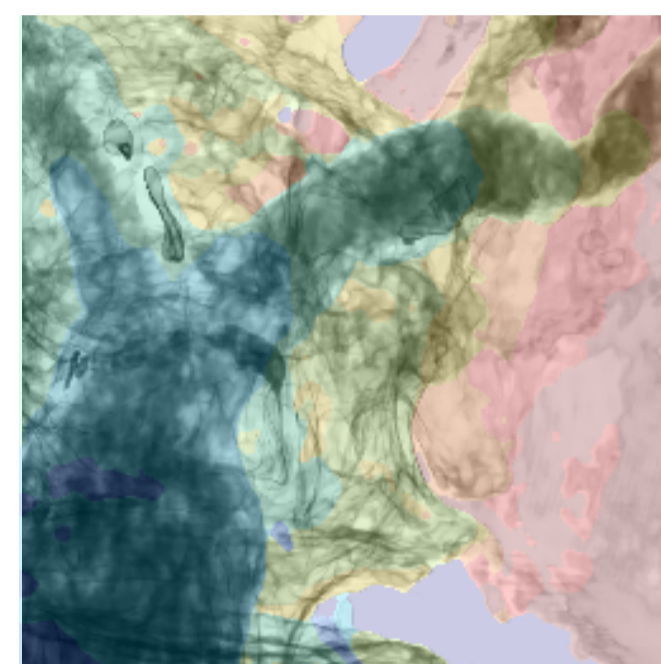
## Towards a Novel Concept for Image-Guided Interventions

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### Overview and Motivation

- X-ray imaging is widely used for guiding minimally-invasive surgeries
- Physicians work at the limit of their perceptual and cognitive abilities [1]
- Correct depth prediction is still hampered due to its projective nature [2]
- Estimated depth of interventional imaging is highly desirable

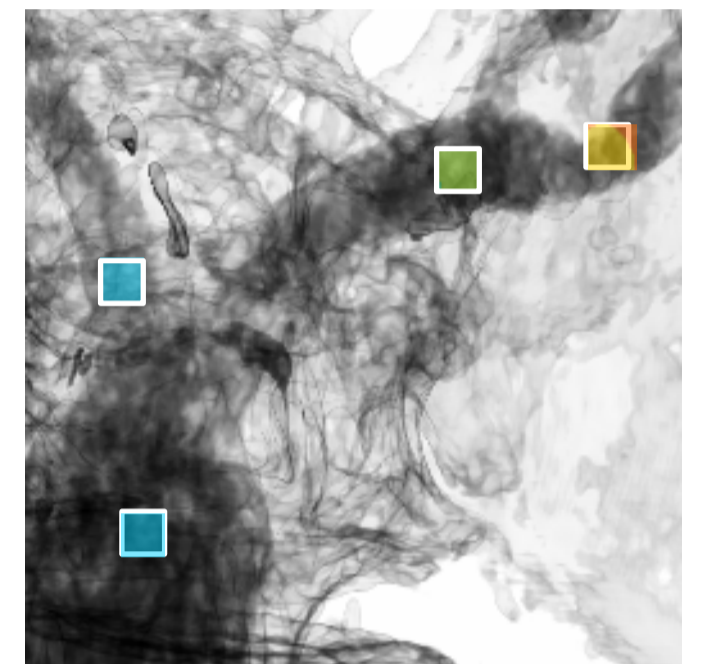


#### Previous attempts:

Virtual and Augmented reality [3],  
Rendering schemes [4-5]

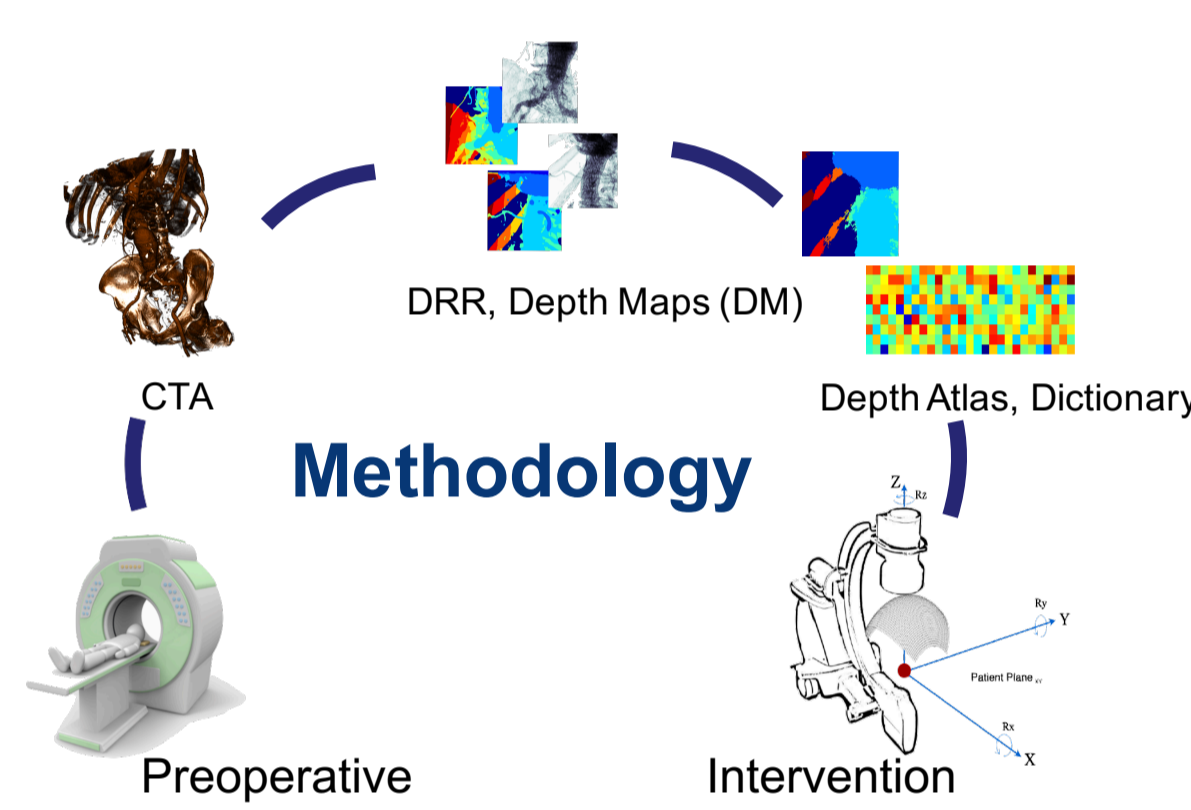
#### Challenges:

Accurate 2D-3D registration [6], Ambiguity



### Methodology:

- Our framework starts with a pre-operative Computed Tomography volume.
- From this, simulated X-ray images together with their corresponding depth maps are rendered.
- For each set of M similar X-ray source configurations, we learn a dictionary and produce a corresponding Depth Atlas.
- These two will be used as prior information for the depth prediction during intervention.



#### 1 Cluster Estimation (C-arm Pose Estimation)

$$\arg \min_{D, \beta_c} \| \text{vec}(I_{p_c}^{DRR}) - D \beta_c \|_2^2 + \delta \| \beta_c \|_1 \quad P_q = \arg \min_{p_c} \| \text{vec}(I_q^{Xray}) - D \beta_{q_c} \|_2^2, \quad c = 1, 2, \dots, M$$

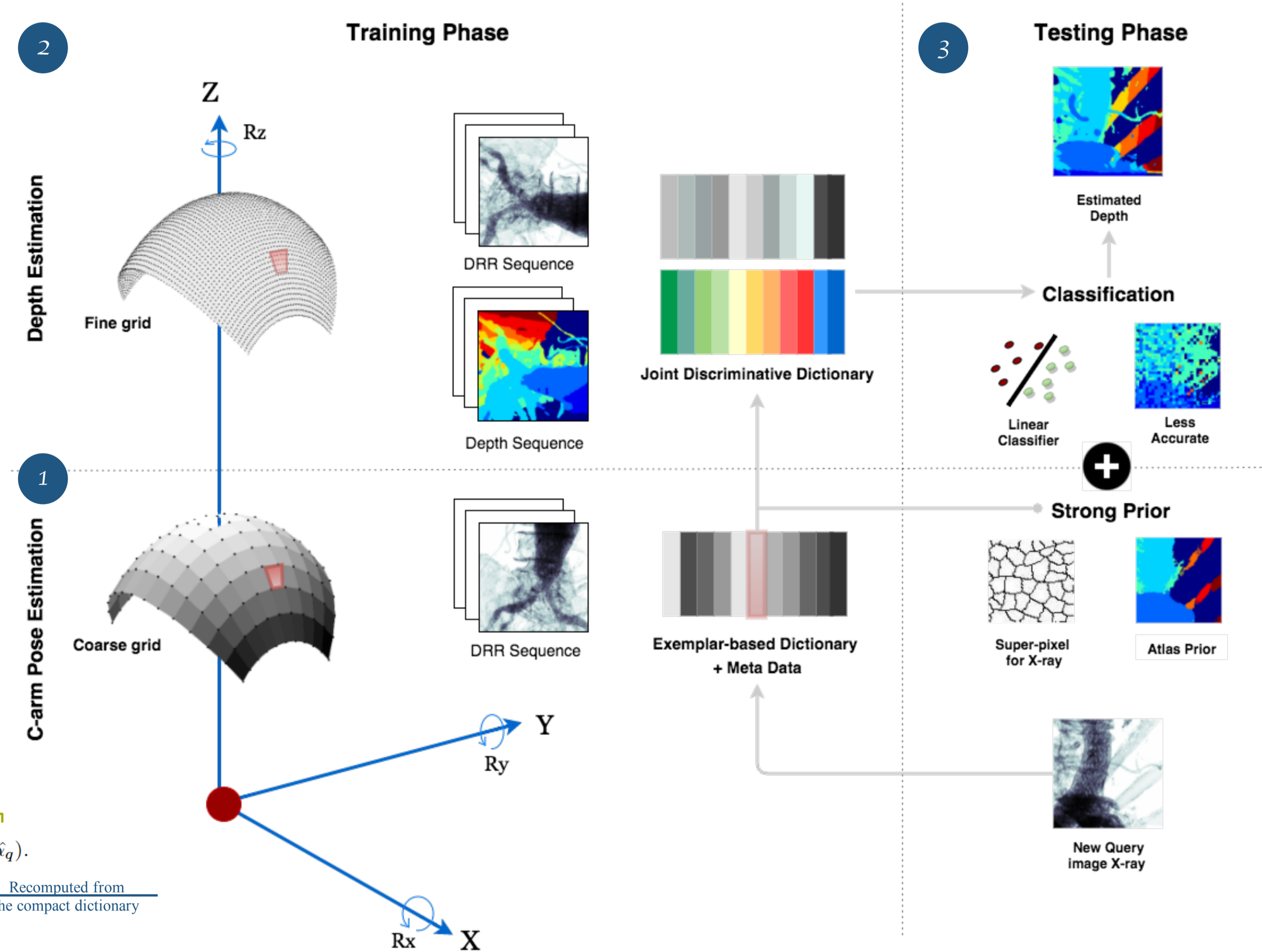
Learned Dictionary      Sparse Codes      Meta data (configuration set) of the most similar dictionary (cluster)

#### 2 Depth Prediction using LCKSVD algorithm [7]

$$\arg \min_{D, \alpha} \left\| \begin{pmatrix} X \\ \sqrt{\gamma} Q \end{pmatrix} - \begin{pmatrix} D \\ \sqrt{\gamma} A \end{pmatrix} \alpha \right\|^2, \quad s.t. \|\alpha\|_0 \leq T, \quad \hat{\alpha}_q = \arg \min_{\alpha} \| X_q - \hat{D} \alpha \|^2, \quad s.t. \|\alpha\|_0 \leq T, \quad p(\hat{y}_q | X_q) = \arg \max_y (y = \hat{W} \hat{\alpha}_q)$$

Compact learned dictionary      Testing Image      Discriminative sparse codes  
Training Data (DRR + DM)      Discriminative sparse codes      Recomputed from the compact dictionary      Predicted class (depth layer)      Recomputed from the compact dictionary

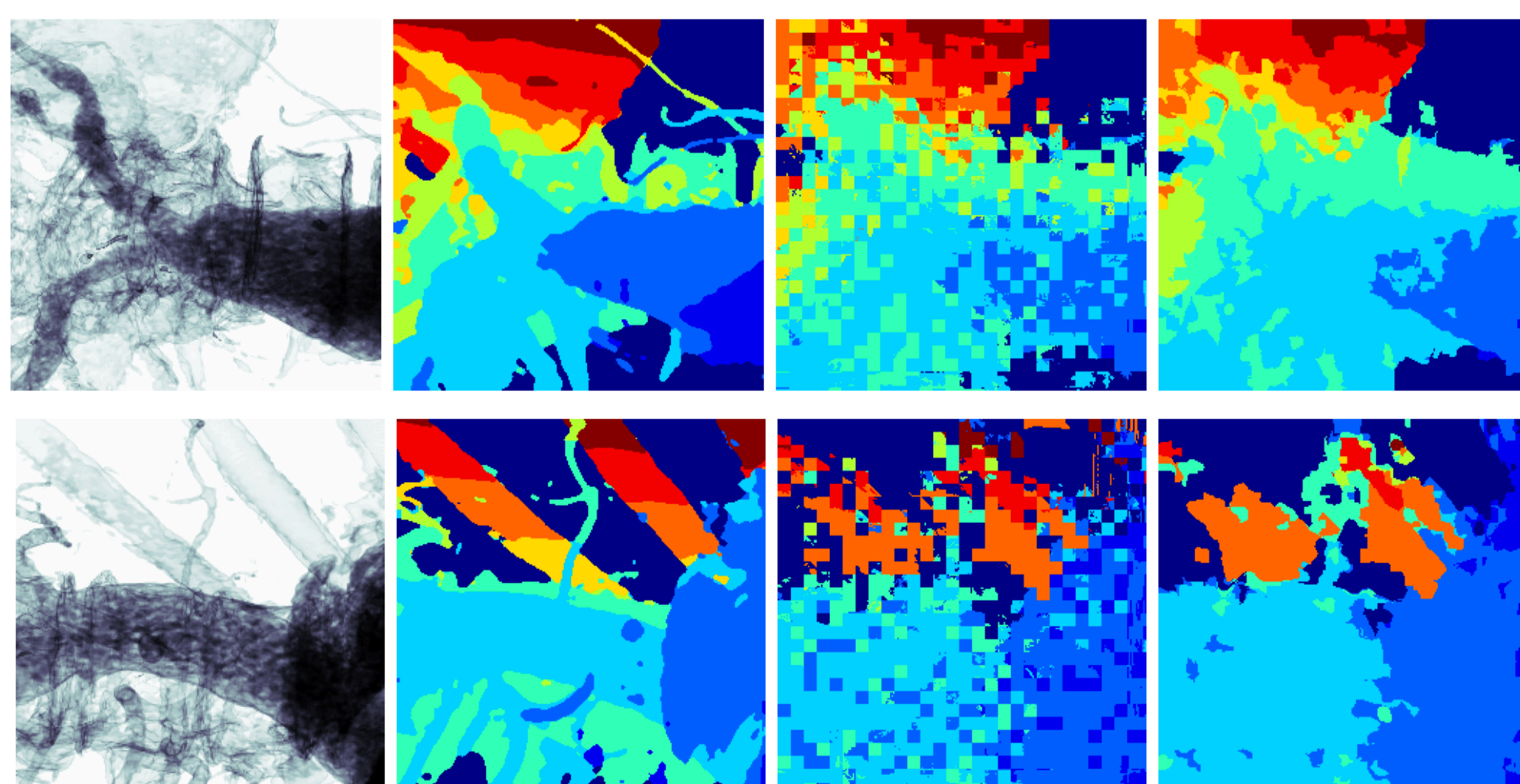
#### 3 Depth Recovery (Prior + Post-processing)



### Experiments & Results:

**Dataset:** Two clinical datasets (Abdomen and Thorax), Depth Maps (DM) - DRR pairs are rendered. Training: 480 DRR-DM pairs, Testing: 120 DRR images.

**Evaluation:** Mean Square Error (MSE), Normalized Cross Correlation (NCC), and Relative Error (RE) are reported.



Results for experimental dataset Abdomen (row 1) and Thorax (row 2)

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Table 1: Cluster estimation validation

Parameter	Experiment 1	Experiment 2	Experiment 3	Experiment 4
offset	[10-20,10-20,10-20]	[10-20,10-20,10-20]	[10-20,10-20,10-20]	[10-20,10-20,10-20]
r (deg)	[10-20,10-20,10-20]	[10-20,10-20,10-20]	[10-20,10-20,10-20]	[10-20,10-20,10-20]
r (mm)	[20-40,20-40,600-1k]	[20-40,20-40,600-1k]	[20-40,20-40,600-1k]	[20-40,20-40,600-1k]
f (mm)	200	200	200	200
Accuracy	99%	90%	94%	88%

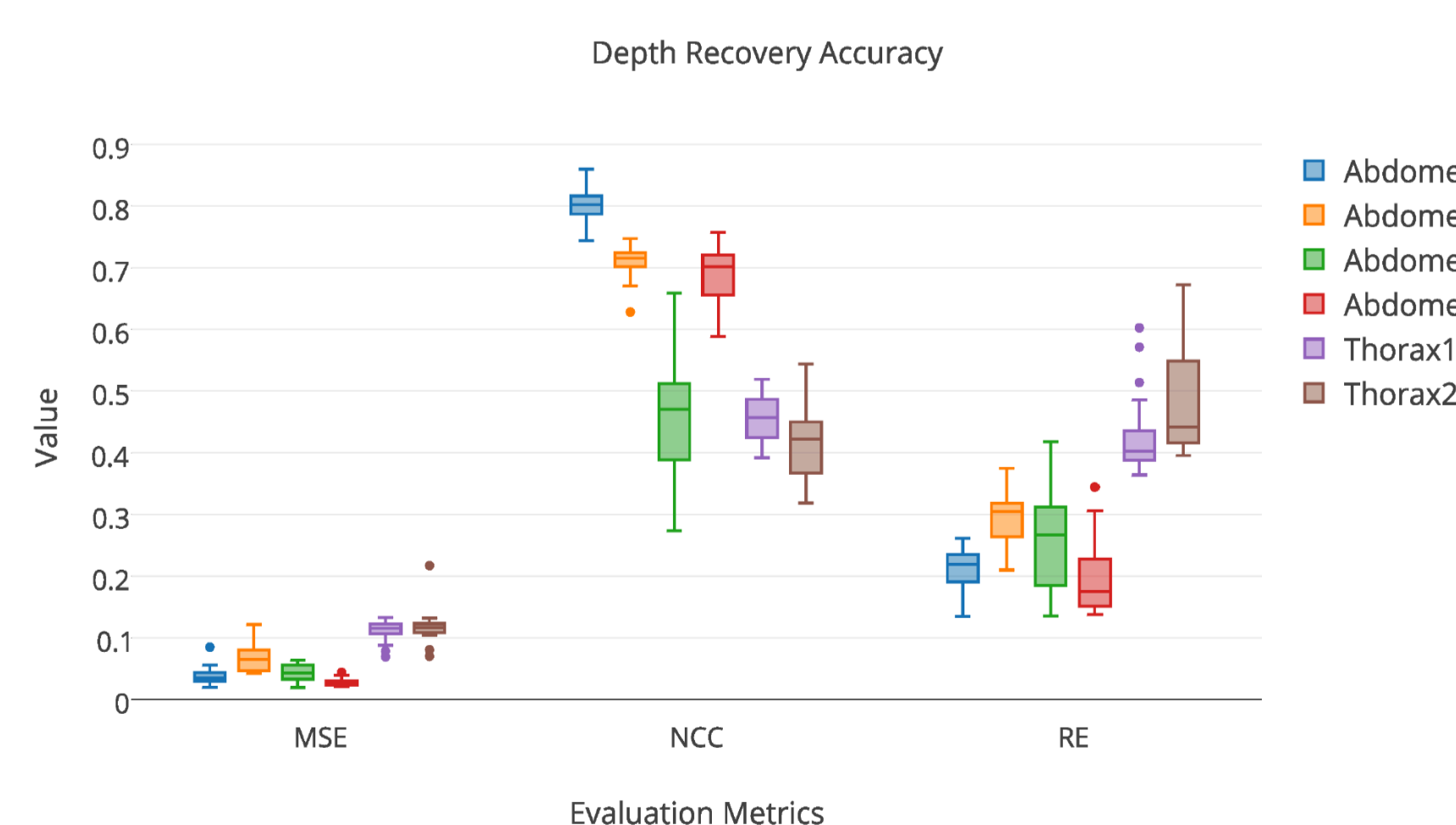


Table 2: The average classification accuracy

Dataset	Configuration set	MSE (100%)	NCC (100%)	Relative Error (100%)
Abdomen	Four	4.40 ± 2.04	66.50 ± 13.94	23.93 ± 6.83
Thorax	Two	11.47 ± 2.27	43.85 ± 5.54	45.22 ± 7.62

### Conclusion:

- We have presented novel concept for Single-View Depth Estimation
- We have achieved around 4.40% ± 2.04 and 11.47% ± 2.27 MSE on abdomen and thorax datasets respectively
- One focus of our future work to use deep learning together with conditional random field (CRF) to get more accurate and smoother depth map [8]
- Importantly, transfer the proposed method to real interventional X-ray images.

### References:

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