DeepCA: Deep Learning-based 3D Coronary Artery Tree Reconstruction from Two 2D Non-simultaneous X-ray Angiography Projections

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Background

(Siemens single-plane C-arm) (C-arm imaging geometry) (ICA images)

- Cardiovascular diseases are the most common cause of death worldwide, representing **32%** of all global death
- X-ray invasive coronary angiography (**ICA**) acquires 2D projections of coronary artery tree (based on C-arm) and is the gold standard during cardiac interventions
- Around **250,000** coronary angiograms are performed across the UK every year

Motivation

- Reduce the likelihood of subjective interpretation of 3D coronary artery tree geometry based on 2D projections
- Reduce extra contrast injected and extra X-ray radiation dose exposed
- Deep Learning Usage:
  - Automated 3D reconstruction in real time
  - **Implicitly compensate** for the non-rigid cardiac and respiratory motions

(Segmented ICA)

Challenges

(Single-plane C-arm Machine Geometry)

- **Non-rigid** cardiac and respiratory motions due to **non-simultaneous image acquisition**, causing vessels to misalign between projections
- Possible patient and device movements between non-simultaneous scans
- Foreshortening, vessel overlap and complex vessel shape
- Only **two** projections acquired and some parts of the vessels in projection images may be incomplete
- Only binary structures and no effective intensity information in projections due to the contrast injected
- **No corresponding 3D ground truth** to real ICA data and the number of real clinical 2D ICA data is also **limited**
- **No prior work** to tackle the non-simultaneous ICA projections using deep learning

Pipeline

Through simulating projections from Coronary Computed Tomography Angiography (**CCTA**) data, we achieve **generalisation** on 3D coronary artery tree reconstruction from two real clinical non-simultaneous ICA projections.

(a) **The data preprocessing block** generates two simulated projections from 3D CCTA data, including simulated motion (**rigid transformations**) between projections, and then produces model input via performing backprojection on two simulated projections.

(b) **The 3D reconstruction with motion compensation block** receives the 3D backprojection input to train a deep neural network for 3D coronary artery tree reconstruction learned from the original CCTA data, **implicitly compensating** for any motion.

Model

Our model architecture is based on the **Wasserstein conditional generative adversarial network** (**WCGAN**) with **gradient penalty** (**WGP**), **latent convolutional transformer** layers (**CTLs**), and a **dynamic snake convolutional critic** (**DSCC**).

- The generator produces corresponding reconstructed results according to the input. The predicted results and the corresponding ground truth are concatenated with the input separately, which are then sent to the critic to generate the critic loss.

✦ The conditional structure of the GAN enables us to generate a desired output from **a specific input condition**

✦ The Wasserstein adversarial objective with gradient penalty improves training **stability**

❖ Since our data contain **large empty background**, usual patch embeddings are not suitable

❖ Built on **convolutional embeddings** following **8** transformer layers in the **latent space** to extract relations between feature maps and enforce their importance

❖ We do not require positional embeddings for feature maps as they are **order invariant**

❖ Apply both **dynamic snake convolution** and traditional convolution in the critic to extract global tubular features and essential local features, effectively **distinguishing vessel tubular structures**

- Via mapping the input with non-aligned projections to 3D coronary tree data, **most motion artifacts are corrected** by our model
- With the critic used, **any residual deformations are adjusted**, while ensuring the connectedness of coronary artery tree structures and increasing the model's elastic **generalisation** capacity
- So when generalising to **clinical non-simultaneous** ICA projections, the **non-rigid** motion is **compensated implicitly**

Evaluation Method

✦ Use a **public CCTA dataset** (ImageCAS) with 3D **segmented** coronary trees for training and collect a **clinical ICA dataset** for evaluation

$$\mathrm{Ot}(t_0) = \frac{|\mathrm{TPM}(t_0)| + |\mathrm{TPR}(t_0)|}{|\mathrm{TPM}(t_0)| + |\mathrm{TPR}(t_0)| + |\mathrm{FN}(t_0)| + |\mathrm{FP}(t_0)|}$$

❖ We use a specific metric designated for this problem in the absence of motion-free 3D ground truth, called **the overlap using a sweeping distance threshold Ot(t_0)** (%), where points of the prediction (**green**) and ground truth (**black**) vessels are labeled as true and false positives or negatives depending on the sweeping test distance $\mathbf{t_0}$ (*mm*).

❖ We also use **the Chamfer ℓ_2 distance** (**CD(ℓ2)**) for measuring the corresponding voxel-wise or pixel-wise prediction errors (*mm*) in either 3D or 2D data.

❖ For the CCTA test dataset, we directly validate the results in 3D space after **rigidly registering** the ground truth to the predicted reconstruction.

❖ We measure the **Dice** score (same as Ot(0)) between the ICA data and reprojections on the first projection plane. For the second and any additional projection planes, **due to motion**, we **first rigidly register** the ICA data to the reprojections and then compute Ot(t_0) and CD(ℓ2) between them.

Results

Model	3D CCTA Test Dataset			2D Real Clinical ICA Dataset (Unseen Domain)						
				1st Projection	2nd Projection			Additional Projection		
	Ot(1)	Ot(2)	CD(ℓ_2)	Dice	Ot(1)	Ot(2)	CD(ℓ_2)	Ot(1)	Ot(2)	CD(ℓ_2)
Un2+ [39]	51.99 (±12.17)	64.75 (±13.28)	4.64 (±2.01)	65.42 (±6.68)	22.97 (±10.82)	31.05 (±12.76)	12.79 (±4.61)	25.25 (±18.40)	39.37 (±20.75)	8.49 (±3.26)
Un3+ [16]	55.10 (±10.72)	68.69 (±10.96)	4.49 (±1.67)	62.23 (±9.49)	22.27 (±8.30)	30.19 (±10.51)	12.20 (±3.77)	32.92 (±23.99)	42.37 (±26.30)	7.70 (±1.59)
DSCN [26]	61.74 (±14.28)	72.21 (±13.31)	3.49 (±1.68)	**83.59** (±4.01)	30.66 (±11.30)	42.74 (±11.68)	7.81 (±2.19)	53.26 (±6.74)	67.90 (±4.77)	3.92 (±0.48)
CVTG [37]	61.53 (±11.49)	73.71 (±10.75)	3.51 (±1.06)	76.84 (±5.73)	32.98 (±12.29)	44.85 (±15.85)	8.23 (±3.73)	49.50 (±0.82)	64.63 (±3.05)	4.22 (±0.51)
DeepCA	**64.21** (±10.78)	**76.25** (±9.72)	**3.22** (±1.20)	83.31 (±4.32)	**45.70** (±6.79)	**58.39** (±8.42)	**4.51** (±1.29)	**58.58** (±4.01)	**72.88** (±0.90)	**2.81** (±0.06)

Four Baselines

Three Ablation Studies

Model	3D CCTA Test Dataset		
	Ot(1)	Ot(2)	CD(ℓ_2)
WGP	62.06 ±10.61	74.38 ±10.01	3.43 ±1.29
+CTLs	62.87 ±11.68	74.39 ±10.70	3.24 ±1.23
+DSCC	63.46 ±10.85	75.14 ±10.00	3.24 ±1.23
DeepCA	**64.21** ±10.78	**76.25** ±9.72	**3.22** ±1.20

From left to right: the comparisons of three patients $P_{1,2,3}$ between ICA data and our reprojections on the **first** and **second** projection planes after rigid registration, and our model's **3D reconstruction results**

(A reconstruction example of **recovering missing features**)

From left to right: the original ICA data, the reprojections on **the additional projection plane**, and the comparisons between them after rigid registration of two patients $P_{3,4}$

(The colour **purple** represents ICA data, **green** the reprojection, and **white** the overlap)