

# **Aortic 3D Deformation Reconstruction**

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Thesis submitted in fulfilment of the requirements for  
the degree of

**Doctor of Philosophy**

under the supervision of  
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# Declaration of Authorship

I, Yanhao Zhang declare that this thesis, is submitted in fulfillment of the requirements for the award of Doctor of Philosophy, in the School of Mechanical and Mechatronic Engineering, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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Signature removed prior to publication.  

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Date: **12-Dec-2021**  

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# *Abstract*

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Endovascular intervention plays an important role for treating peripheral arterial diseases. As a minimal invasive surgery treatment, the endovascular intervention provides an alternative to the open surgery with smaller incisions and broadens the options for patients with multiple comorbidities who have higher risk for an open surgery. The minimal invasive treatments benefit patients with low risk and quick recovery. But they also bring challenges to the surgeons: the surgical catheters need to be manipulated precisely inside patient's artery during the treatment.

Clinical endovascular interventions typically rely on X-ray fluoroscopy to provide a live 2D view for catheter manipulation. However, this 2D view cannot fully reflect the vessel's 3D shape as the information along one dimension cannot be visualized. Although a 3D model reflecting aortic 3D shape can be obtained from the pre-operative CT imaging, it cannot be used as an intra-operative guidance since the aorta deforms during the operation. Therefore, an accurate visualization of aortic 3D shape is helpful.

The aim of our research is to study the deformation reconstruction techniques and develop efficient frameworks to recover aortic 3D shape intra-operatively.

In our first research, an initial aortic 3D deformation reconstruction framework is proposed. The main idea is to estimate the warp field of aortic deformation based on embedded deformation graph. The conventional embedded deformation graph requires 3D observation

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as the control points. In our work, we introduce a 2D-3D non-rigid correspondence process which passes the observation information to the deformation graph. Having the correspondence, the deformation estimation is formulated as a non-linear optimization problem that can be solved iteratively using Gauss-Newton method. Our method estimates aortic deformation from the X-ray images, which contain many partial occlusions and background artefacts. This means the intensity from the X-ray image does not always represent correct information for our problem. Therefore, semantic features are needed. To tackle this problem, we use the pixels presenting the vessel wall contours as the features. We also show the influence of the image number to the reconstruction accuracy, and demonstrate that our framework is able to recover vessel's 3D shape with high accuracy using only two images.

In our second research, we improve our initial framework from two aspects. First, the feature selection process is performed according to a deep learning based image segmentation. This makes our framework fully automatic for aortic intra-operative reconstruction. Second, a signed distance field based correspondence method is used. This helps avoid the repeated vertex-feature non-rigid correspondence while the matching accuracy is maintained. Compared with our first work, the second framework reconstructs aortic 3D deformation automatically and computationally more efficiently.

The accuracy of our framework is further improved in our third research. The main idea is to combine the aortic centreline reconstruction together with the vessel's shape reconstruction. First, the pixels of aortic 2D centreline are extracted from each image using a deep learning based image segmentation. A distance field is then built using the 2D centreline. Using the distance field, the 3D deformation of aortic centreline is reconstructed. After this, using the reconstructed centreline, the vessel's 3D shape is initially reconstructed. Finally, the vessel's 3D shape as well as the 3D centreline is refined using the similar method as our second framework. Since the initial shape is close to the final result, the vertex-feature matching is greatly improved, which results in a more robust reconstruction of aortic 3D deformation.

Detailed real phantom experiments are conducted for all of the proposed frameworks, and the results demonstrate the reconstruction accuracy. We believe our research has the

potential to benefit the endovascular interventions.

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# Acronyms & Abbreviations

<b>AAA</b>	Abdominal Aortic Aneurysm
<b>EVI</b>	Endovascular Interventions
<b>EVAR</b>	Endovascular Aortic Repair
<b>MIS</b>	Minimally Invasive Surgery
<b>CT</b>	Computed Tomography
<b>MRI</b>	Magnetic Resonance Imaging
<b>OSR</b>	Open Surgical Repair
<b>PPA</b>	Positioner Primary Angle
<b>PSA</b>	Positioner Secondary Angle
<b>LAO</b>	Left Anterior Oblique
<b>RAO</b>	Right Anterior Oblique
<b>CRA</b>	Cranial Angle
<b>CAU</b>	Caudal Angle
<b>SLAM</b>	Simultaneous Localisation and Mapping
<b>MNT</b>	Moore Neighbour Tracing
<b>MN</b>	Moore Neighbourhood
<b>DF</b>	Distance Field

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<b>SDF</b>	Signed Distance Field
<b>CUDA</b>	Compute Unified Device Architecture
<b>ED graph</b>	Embedded Deformation Graph
<b>ED node</b>	Graph Node of Embedded Deformation Graph
<b>GN</b>	Gauss-Newton
<b>DLB</b>	Dual Quaternion Linear Blending
<b>ARAP</b>	As Rigid As Possible
<b>CNN</b>	Convolutional Neural Network
<b>ReLU</b>	Rectified Linear Unit
<b>BN</b>	Batch Normalisation
<b>FCN</b>	Fully Convolutional Network
<b>ICP</b>	Iterative Closest Point
<b>ECG</b>	Electrocardiogram
<b>TPS</b>	Thin Plate Spline
<b>GPU</b>	Graphics Processing Unit
<b>TSDF</b>	Truncated Signed Distance Field
<b>SURF</b>	Speeded Up Robust Features
<b>FEM</b>	Finite Element Method
<b>NRSfM</b>	Non-Rigid Structure from Motion

# Nomenclature

## General Notations

$\mathbb{R}^n$	The $n$ -dimensional Euclidean space
$\text{SO}(3)$	The special orthogonal group
$\text{SE}(3)$	The special Euclidean group
$\mathbf{I}_n \in \mathbb{R}^{n \times n}$	The identity matrix
$ \cdot $	Number of elements in a set
$\ \cdot\ $	Euclidean norm of a vector
$\mathbf{g}_j \in \mathbb{R}^3$	The position of ED node $j$
$\mathbf{A}_j \in \mathbb{R}^{3 \times 3}$	The affine matrix of ED node $j$
$\mathbf{t}_j \in \mathbb{R}^3$	The translation of ED node $j$
$\mathbf{p} \in \mathbb{R}^3$	The position of a 3D Point
$g(\cdot)$	The deformation function of ED graph
$q(\cdot)$	The camera projection function
$w_j(\mathbf{p})$	The weight quantifying the influence of node $j$ to a point $\mathbf{p}$
$E_{\text{rot}}, E_{\text{reg}}, E_{\text{mea}}$	The rotation/regularisation/measurement term to solve ED graph
$\mathbf{m}_i, \tilde{\mathbf{m}}_i$	The original and new position of a control point $i$
$\mathbf{v}_i$	The 3D position of vertex $i$ from a polygonal mesh
$\hat{\mathbf{v}}_i$	The estimated new position of a vertex
$\mathbf{b}_i \in \mathbb{R}^2$	A boundary feature pixel $i$ from X-ray image $I_l$
$\mathbf{n}(\cdot)$	2D normal vector of a point.
$\tilde{\mathbf{n}}(\cdot)$	3D normal vector of a point.
$\mathbf{g}_{ij}^l \in \mathbb{R}^2$	The coordinate of a grid cell to calculate SDF on image $I_l$
$\mathbf{f}_i \in \mathbb{R}^2$	An ordered centreline feature pixel $i$ from X-ray image $I_l$



$\mathbf{t}(\cdot)$	2D tangent vector of a point on centreline.
$\check{\mathbf{t}}(\cdot)$	3D tangent vector of a point on centreline.
$\mathbf{c}_i$	The 3D position of a centreline point $i$