Aortic 3D Deformation Reconstruction

by Yanhao Zhang

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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.

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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 alone 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

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

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

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

Nomenclature

	General Notations
$\mathbb{R}^n$	The n-dimensional Euclidean space
$\mathbb{SO}(3)$	The special orthogonal group
$\mathbb{SE}(3)$	The special Euclidean group
$\mathbf{I}_n \in \mathbb{R}^{n\times n}$	The identity matrix
$\lvert \cdot \rvert$	Number of elements in a set
$\lVert \cdot \rVert$	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 $\mathbf{p}$
$E_{\mathrm{rot}}, E_{\mathrm{reg}}, E_{\mathrm{mea}}$	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
$\mathbf{b}_{l_i} \in \mathbb{R}^2$	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.
$\mathbf{g}^l_{ij} \in \mathbb{R}^2$	The coordinate of a grid cell to calculate SDF on image I_l
$\mathbf{f}_{l_i} \in \mathbb{R}^2$	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