Real-Time 3-D Shape Instantiation for Partially Deployed Stent Segments From a Single 2-D Fluoroscopic Image in Fenestrated Endovascular Aortic Repair

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Abstract—In fenestrated endovascular aortic repair (FEVAR), accurate alignment of stent graft fenestrations or scallops with aortic branches is essential for establishing complete blood flow perfusion. Current navigation is largely based on two-dimensional (2-D) fluoroscopic images, which lacks 3-D anatomical information, thus causing a longer operation time and high risks of radiation exposure. Previously, 3-D shape instantiation frameworks for real-time 3-D shape reconstruction of fully deployed or fully compressed stent grafts from a single 2-D fluoroscopic image have been proposed for 3-D navigation in FEVAR. However, these methods could not instantiate partially deployed stent segments, as the 3-D marker references are unknown. In this letter, an adapted graph convolutional network (GCN) is proposed to predict 3-D partially deployed marker references from 3-D fully deployed marker references. As the original GCN is for classification, in this letter, the coarsening layers are removed and the softmax function at the network end is replaced with linear mapping for regression. The derived 3-D marker references and the 2-D marker positions are used to instantiate the partially deployed stent segment, combined with the previous 3-D shape instantiation framework. Validations were performed on three typical stent grafts and five patient-specific 3-D printed aortic aneurysm phantoms. Reasonable performances with average mesh distance errors from 1.0 to 2.4 mm and average angular errors around 7.2° were achieved.

Index Terms—Deep learning in robotics and automation, computer vision for medical robotics, surgical robotics: planning, visual-based navigation, motion and path planning.

I. INTRODUCTION

ABDOMINAL Aortic Aneurysm (AAA), an enlargement of the abdominal aorta with 50% diameter over the normal state, occurs increasingly in aging population [1]. The rupture of AAA brings in 85%–90% fatality rate [2]. Fenestrated Endovascular Aortic Repair (FEVAR) is a minimally invasive surgery for AAA, where a deployment catheter carrying a compressed stent graft is inserted via the femoral artery, advanced through the vasculature and deployed at the AAA position [3]. Three typical stent grafts - iliac, thoracic and fenestrated stent graft are shown in Figures 1(a), 1(b) and 1(c) respectively. In FEVAR, an accurate alignment of stent graft fenestrations (a circular or elliptical hole placed below the proximal fabric margin of the graft) or scallops (a U-shaped gap in the proximal fabric) (as shown in Figure 1(c)) to aortic branches, i.e., renal arteries, is necessary for connecting branch stent grafts into aortic branches [3]. Although several robot-assisted systems have been developed to facilitate the FEVAR procedure, i.e., the Magellan system (Hansen Medical, CA, USA), the current navigation technique is still based on 2D fluoroscopic images, as shown in Figure 1(e), where blurred outlines and insufficient depth information are not efficient for an accurate 3D-to-3D alignment. Thus, 3D shape recovery based on limited 2D images, called shape instantiation, is required for surgical navigation.

A skeleton-based as-rigid-as-possible approach was proposed to adapt a pre-operative 3D AAA shape to intra-operative position of the deployment device from two fluoroscopic images for 3D AAA shape recovery [4]. A skeleton instantiation framework for AAA with a graph matching method and skeleton deformation was introduced to instantiate the 3D AAA skeleton from a single 2D fluoroscopic image [5]. These methods provide...
3D spatial information of AAA which is essential for FEVAR navigation.

For offering 3D spatial information of fenestrated stent grafts, many methods have been implemented. The 3D stent shape was recovered from a 2D X-ray image via registration and optimization in [6] but without estimation of the graft nor the angle or position of fenestrations or scallops. A 3D shape instantiation framework with stent graft modelling and Robust Perspective-n-Point (RnP) method was proposed to instantiate the 3D shape of a fully-compressed stent graft [7]. The work in [7] was then used to recover the 3D shape of each stent segment with customized markers, while Focal U-Net and graft gap interpolation were proposed to semi-automatically segment customized markers and recover the whole 3D shape of fully-deployed stent grafts in [8]. Equally-weighted Focal U-Net was later proposed for automatic marker segmentation in [9]. However, these methods could not instantiate the 3D shape of a partially-deployed stent segment, as the 3D marker references are unknown.

The method in this letter aims for automatic prediction of the unknown 3D marker references via extracting the deformation pattern between partially-deployed and fully-deployed marker references. The conventional convolution neural networks is not suitable in this task, as the movement relationships between different two markers are not equivalent and the topological structure is non-Euclidean. A novel convolution on an undirected simple graph called spectral graph convolution was described in [10]. Graph Convolutional Network (GCN) with locally connected architecture was then proposed based on the spectrum of graph Laplacian, which was validated on the MNIST dataset [11]. A more efficient GCN with localized spectral convolution via a kernel fitted by the polynomial of a Laplacian matrix was proposed in [12], reducing the parameter number with improved performance. Another construction of GCN was with the first-order approximation of spectral graph convolutions for a large-scale architecture, but with less capacity for the same layer number [13].

An adapted GCN based on the architecture in [12] is proposed for predicting 3D partially-deployed marker references from 3D fully-deployed marker references, which bridges the gap of utilizing the 3D shape instantiation framework in [8] for partially-deployed stent segments. The coarsening layers are removed and the softmax function at the network end is replaced with a linear mapping. The derived 3D partially-deployed marker references are integrated into [8], with the customized marker placement, stent segment modelling and the RnP method, to achieve 3D shape instantiation for partially-deployed stent segments. Three stent grafts with totally 26 different stent segments were used for the validation. Details regarding the methodology and experimental setup are in Sec. II. Results including an average angular error about 7.2° and an average mesh distance error around 1.9 mm are stated in Sec. III. Discussion and conclusion are in Sec. IV and Sec. V respectively.

II. METHODOLOGY

As shown in Figure 2, the shape instantiation framework for partially-deployed stent segment is divided into pre-and intra-operative stages. In the pre-operative stage, 3D partially-deployed marker references are predicted from 3D fully-deployed marker references which are extracted from pre-operative Computerized Tomography (CT) scan or stent graft design with the proposed adapted GCN. In the intra-operative stage, following [8], the predicted 3D marker positions and 2D marker positions extracted from the fluoroscopic image are used to instantiate the 3D stent segment shape. In this section, we introduce the proposed adapted GCN for predicting 3D marker references, while briefly introducing the stent segment modelling and 3D shape instantiation to facilitate framework understanding. The experimental setup is also demonstrated.

A. Partially-Deployed Stent Segment Modelling

In practice, the parameters of a stent segment, including the height and diameters at fully-deployed and fully-compressed state, can be obtained via stent graft and deployment catheter design. In this letter, as stent grafts were experimented multiple times with compression and deployment, the practical parameters are different from the ideally designed ones and are measured with CT scan.

The diameters of partially-deployed stent segments are decided by the designed deployment size, the compression diameters $r_{fc} \in \mathbb{R}_+$ and the gap width $w_g \in \mathbb{R}_+$. In the experiments, the diameter at its deployed side $r_{pd} \in \mathbb{R}_+$ is set as the value designed for fully-deployed state $r_{id} \in \mathbb{R}_+$: $r_{pd} := r_{id}$. The diameter at its compressed side $r_{pc} \in \mathbb{R}_+$ is set as the minimum value between the deployed diameter, and the addition of compressed diameter and twice gap width: $r_{pc} := \min\{r_{fc} + 2w_g, r_{id}\}$. Then, a cone shape fitted by a series of concentric circles with a finite set of vertices $V$ of coordinates $V \in \mathbb{R}^{3\times(360h/0.1\text{ mm})}$ is modelled for the partially-deployed stent segment, with the resolution of height $h$ and rotation angle $\theta$ set as 0.1 mm and 1°. The coordinate of each circle vertex is defined as $(r_{pc} \sin \theta \ r_{pc} \cos \theta \ h)^{\top}$. Following [8], these circle vertices are accumulated by connecting the neighbouring vertices regularly into triangular faces, resulting in a mathematically modelled stent segment mesh. Fenestrations or scallops are modelled by
removing the corresponding vertices and triangular faces. A set of five customized markers are sewn on each stent segment. With known pre-operative 3D marker positions (3D references) and corresponding intra-operative 2D marker positions (2D references), the 3D intra-operative pose of marker set which is also the 3D intra-operative pose of the stent segment could be recovered by the RPhP method [8]. Details regarding this part will be briefly introduced in Sec. II-C.

Unlike the work in [7] and [8] for fully-compressed and fully-deployed stent segments, where 3D marker references are known from CT scan or stent graft design, 3D marker references for partially-deployed stent segments are unknown due to the unpredictability of the deployment process.

B. Adapted GCN

With known pre-operative 3D fully-deployed marker references $Y^i = (y^i_1 \cdots y^i_N) \in \mathbb{R}^{3 \times N}$, an adapted GCN for regressing pre-operative 3D marker references of partially-deployed stent segment $Y^i_p \in \mathbb{R}^{3 \times N}$ is proposed based on [12]. The original GCNs in [12] and [13] were used for classification tasks, with coarsening layers for down-sampling and a softmax function and a threshold function at the network end for logic value output. In this letter, the graph structure of the input is the same as the output, the coarsening layers are removed. The softmax function and the threshold function are replaced by linear mapping for regression of the latent mapping between fully- and partially-deployed marker references.

1) Data Pre-Processing: There are two steps to minimize the influence of frame transformation and focus the adapted GCN training on learning the deformation between $Y^1$ and $Y^i_p$. Firstly, the markers’ coordinates for fully-deployed stent segment $Y^i$ are standardized in the local frame with the transformation: $\tilde{t}_f^i := \sum_{l=1}^5 (y^i_l)$ and, $R^i := \left( v_1/\|v_1\| 2 v_2/\|v_2\| 2 v_3/\|v_3\| 2 \right)$, where $v_1 := y^i_1$, $v_2 := (y^i_1 \times y^i_2)$, $v_3 := (v_1 \times v_2)$ and $Y^i := R^i Y^i_f \times$ between two vectors represents the cross product. The transformation between global frame and local frame can be thus represented as: $Y_p^i = R^i Y^i_f + t_f^i \otimes (1)_{1 \times 5}$, where $\otimes$ is the kronecker product and $(1)_{1 \times 5}$ is a 1 × 5 matrix consisting of 1.

Secondly, the ground truth of the markers’ coordinates for each partially-deployed stent segment in global frame $Y_p^i$ is transformed in the local frame $Y_p^i$ by aligning to the markers for the corresponding standardized fully-deployed stent segment $Y^i$ via singular value decomposition (SVD): $U_{svd} Y^i_{svd} = Y_p^i \otimes Y^i_f$. The aligned markers’ coordinates for each partially-deployed stent segment is thus calculated with mapping $f : (\mathbb{R}^{3 \times 5}, \mathbb{R}^{3 \times 5}) \rightarrow \mathbb{R}^{3 \times 5}$ defined as: $Y_p^i = f (Y_p^i, Y^i_f) := R_{i \times 5}^i Y_p^i + t_{i \times 5}^i$, where $R_{i \times 5}^i := V_{svd} U_{svd}$ and $t_{i \times 5}^i := \sum_{l=1}^5 (y^i_l) - R_{i \times 5}^i \sum_{l=1}^5 (y^i_l)$ are the rotation matrix and translation vector of the transformation.

2) Network Architecture: The number of five customized markers is shown in Figure 1(d). An undirected simple graph $G = (V, E, W)$ is constructed to represent the five markers’ coordinates with $n = 5$ nodes, where $V$ is a finite set of $|V| = n$ vertices, $E \subseteq V \times V$ is a set of edges, $W \in \mathbb{R}^{n \times n}$ is the weighted adjacency matrix referring to the distance scale:

$$W = \begin{bmatrix}
0 & e^{-(5/4)^2} & 0 & 0 & e^{-(5/4)^2} \\
0 & 0 & e^{-(5/4)^2} & 0 & 0 \\
e^{-(5/4)^2} & 0 & e^{-(5/4)^2} & 0 & 0 \\
e^{-(5/4)^2} & 0 & 0 & e^{-(5/4)^2} & 0 \\
e^{-(5/4)^2} & 0 & 0 & 0 & e^{-(5/4)^2}
\end{bmatrix}$$ (1)

The network architecture is shown in Figure 3, where the input is $Y^i_f$ and the output is $Y^i_p$. The mathematical expression for each two neighbouring layers can be written as:

$$F_{i+1} = \sigma_i ((g_\theta \ast F_i)_{\phi})$$ (2)

where $i \in \{0, N\} \cap \mathbb{Z}$, $F^0$ is the input graph, $F^{N+1}$ is the output graph, $F^{[1, N]}$ are hidden layers, $N$ is the hidden layer number and $\sigma_i(\cdot)$ is the activation function for the $i^{th}$ layer, the spectral convolution on the graph $G$ is defined as:

$$(g_\theta \ast F^i)_{\phi} := F_{\phi}^{-1} (F_{\phi} (g_\theta) F_{\phi} (F^i)) = U g_\theta U^T F^i$$ (3)

where $g_\theta = U^T g_\phi$ is the Fourier transformed convolution kernel with the trainable parameters $\theta \in \mathbb{R}^{K \times (N+1)}$ using Chebyshev polynomials recursive calculation to reduce the time complexity, $K \in \mathbb{Z}_+$ is the kernel size, $U$ is the eigen vectors of the normalized Laplacian matrix of $G$: $L := D^{-1/2}(D - W) D^{-1/2}$, and $D$ is the diagonal degree matrix. The detail derivation is described in [11] and [12].

Eight hidden layers are used for the experiments, 32 channels are set in each hidden layer. Leakly ReLU [14] is used as the activation function for non-linear mapping with 0.1 leaky rate for the input and the hidden layers. No non-linear activation function is used in the output layer. Chebyshev polynomial parametric kernel is used with a kernel size of 2 for each spectral convolutional layer.

3) Loss Function and Optimization: The root mean square error between the ground truth and the output coordinates is calculated as the loss function, with a regularization term of L2 norm of the weight matrix:

$$L = \| Y_{p}^{i} - Y_{p}^{i} \|_2 + \alpha \| \theta \|_2$$ (4)

The weight parameters $\theta$ were initialized randomly as described in [15]. Adam and Momentum Stochastic Gradient Descent (SGD) were compared for training the network. The optimization through Adam was hard to converge and hence Momentum SGD was used as the optimizer. The learning rate was set as 0.0001 and the learning momentum was set as 0.9. The L2 norm
weight $\alpha$ was set as $5 \times 10^{-4}$ and the batch size was set as 10. The training process was stopped when the loss stopped decreasing.

As the RPNp method is only related to 3D reference marker shapes while is free to global 3D reference marker positions, the predicted 3D marker references $\hat{Y}_p^f$ are aligned to the local markers’ coordinates of fully-deployed stent segment $Y_l^f$ as $f(Y_p^f, Y_l^f)$ for the transformation estimation of the partially-deployed stent segments.

### C. 3D Shape Instantiation

With the predicted pre-operative 3D marker references from the adapted GCN in Sec. II-B and manually labelled corresponding intra-operative 2D marker positions, following [8], the RPNp method [16] is used to instantiate the 3D pose of intra-operative marker set including the rotation matrix $\hat{R}_l^f \in \mathbb{R}^{3 \times 3}$ and translation vector $\hat{t}_l^f \in \mathbb{R}^3$: $\hat{Y}_l^f = \hat{R}_l^f f(Y_p^f, Y_l^f) + \hat{t}_l^f \otimes (1)_{1 \times 3}$, where $Y_p^f$ is the instantiated intra-operative 3D marker positions for partially-deployed stent segment. As markers are sewn on the stent segment, $\hat{R}_l^f$ and $\hat{t}_l^f$ are also the rotation matrix and translation vector for the partially-deployed stent segment. After moving the mathematically modelled stent segment mesh in Sec. II-A to the same local coordinate frame, $\hat{R}_l^f$ and $\hat{t}_l^f$ are applied for the stent segment transformation. After central point based correction, 3D shape instantiation of partially-deployed stent segment is achieved. More details could be found in [8].

### D. Experiment and Validation

1) **Marker Design:** Customized stent graft markers with five different shapes were designed based on commercially-used gold markers and were manufactured on a Mlab Cusing R machine (ConceptLaser, Lichtenfels, Germany) from SS316L stainless steel powder, as shown in Figure 1(d) with their own numbers. The sizes are around [1, 3] mm, similar to the commercial ones. Those five markers were sewn on each stent segment at five non-planar places.

2) **Simulation of Surgery:** Three stent grafts were used in the experiments, including a iliac stent graft (Cook Medical, IN, USA) with five stent segments, [10, 19] mm diameters and total 90 mm height, a fenestrated stent graft (Cook Medical) with six stent segments, [22, 30] mm diameters and total 117 mm height, and a thoracic stent graft (Medtronic, MN, USA) with 10 stent segments, 30 mm diameter and total 179 mm height. Five AAA phantoms were modelled from CT data scanned from patients and were printed on a Stratasys Object 3D printer (MN, USA) with VeroClear and TangoBlack colours. The stent grafts and phantoms are the same as the ones used in [8], however, all experiments were re-performed. To simulate the practical situation in FEVAR where the fenestrated stent graft is customized to similar diameters to that of the AAAs, two suitable AAA target positions where their diameters are similar to that of the corresponding experiment stent graft were selected for each experiment stent graft, resulting in 6 experiments in total. The selected AAA phantom was fixed as shown in Figure 4. In each experiment, a stent graft was compressed into a Captivia delivery catheter (Medtronic) with 8 mm diameter, inserted into the selected phantom and deployed subsequently segment-by-segment from the proximal end to the distal end at the target AAA position.

3) **Data Collection:** A 3D CT scan and a 2D fluoroscopic image at the frontal plane were scanned for each partially-deployed stent graft using a GE Innova 4100 (GE Healthcare, Bucks, UK) system. The stent segments at the distal end and with odd indexes in the thoracic stent graft experiment were ignored to keep data balance. Thus, there are eight partially-deployed stent segments scanned by CT and fluoroscopy in two different AAA phantoms for the iliac stent graft (segment number 1–4 and 5–8), 10 for the fenestrated stent graft (segment number 9–13 and 14–18), and eight for the thoracic stent graft (segment number 19–22 and 23–26). In addition, three CT scans were acquired for the three experiment stent grafts at fully-deployed state to supply 3D fully-deployed marker positions $-Y_l^f$. In practical applications, this information can be obtained from stent graft designing.

4) **Marker Position Extraction:** Although Equally-weighted Focal U-Net was proposed to potentially achieve automatic 2D marker segmentation and classification from intra-operative 2D fluoroscopic images. In this letter, the stent graft is in the partially-deployed state which different from the training data in [9] where the stent graft was in the fully-deployed state. The segmentation and classification results of applying the trained model in [9] onto the fluoroscopic images in this letter is unsatisfying. Hence the intra-operative 2D marker position references were extracted manually via Matlab. The shapes of 3D stents and 3D customized markers were segmented from CT scans via ITK-SNAP and the 3D central coordinates of customized markers were extracted using Meshlab.

5) **Data Augmentation:** Before training the adapted GCN with the 3D marker positions of fully-deployed and partially-deployed stent segments, these coordinates were rotated and scaled to enlarge the training dataset. The rotations about three axes range from $-30^\circ$ to $30^\circ$ with the resolution of $3^\circ$. The scale ratios range from 0.20 to 5.13 with the geometric proportion of 1.5. Gaussian noise $\epsilon \sim N(0, 0.1)$ was also added to the input $Y_l^f$ at the training phase.

6) **Baseline and Comparative Model:** The fully-deployed stent segments were used without deformation as the 3D reference of the partially-deployed state for the baseline of the validation (Non-deformed instantiation). An Artificial Neural Network (ANN) was also used as a model for comparison. It was implemented in Matlab using Deep Learning toolbox with the Levenberg-Marquardt optimization algorithm. The number of

![Fig. 4. Illustration of the experimental setup with fixing an AAA phantom.](image-url)
hidden neurons was increased until the validation error reached a minimal value. The optimized number of hidden neurons is 10. The training data and testing data are the same as those used in the adapted GCN.

7) Criteria and Evaluation: To evaluate the predicted 3D marker references, the aligned 3D marker reference predictions \( \hat{Y}_p \) were compared to the ground truth of the aligned partially-deployed stent segment’s marker positions \( f(Y_p, Y^l) \) via their mean distance error, \( \text{MDE}(Y_p, f(Y_p, Y^l)) \), which is calculated as:

\[
\text{MDE}(Y^1, Y^2) = \frac{1}{n} \sum_{i=1}^{n} \|y_i^1 - y_i^2\|_2
\]

where \( Y^1 \) and \( Y^2 \) can be two matrices of 3D or 2D marker references with the same dimension number and the same point number.

To evaluate marker instantiation, the registered global markers’ coordinates for each partially-deployed stent segment \( Y^g_p \) are compared with the ground truth \( Y_p^g \) via \( \text{MDE}(Y^g_p, Y^g_p) \) in 3D and the reprojected distance error \( \text{MDE}(X_p^g, \hat{X}^g_p) \) in 2D, where \( \hat{X}^g_p \) is the reprojected 2D coordinate from the estimated 3D global coordinate \( Y^g_p \), calculated by \( X^g_p = g(Y_p^g) \) with mapping \( g : \mathbb{R}^{3 \times n} \rightarrow \mathbb{R}^{2 \times n} : g(Y) = (p_1 Y^h \circ p_2 Y^h, p_3 Y^h) \), where \( P = \begin{pmatrix} p_1 & p_2 & p_3 \end{pmatrix} \in \mathbb{R}^{3 \times 4} \) is the projection matrix, \( \circ \) is Hadamard division, and \( Y^h = \begin{pmatrix} y_1^h & \cdots & y_n^h \end{pmatrix} \in \mathbb{R}^{4 \times n} \) is the homogeneous vector form of the 3D coordinates.

To evaluate 3D shape instantiation for each partially-deployed stent segment, the distance between the instantiated partially-deployed stent segment mesh and the corresponding ground truth was measured using Matlab function \text{point2trimesh} [17]. Marker angle was estimated by the angle of the nearest vertex on the constructed stent segment. Mean absolute angle difference between the predicted markers and the ground truth was used to measure the angle error.

8) Cross Validation: Three-fold cross validations were performed along the division of stent graft. For example, for testing stent segments from iliac stents, those from the fenestrated and thoracic stent graft were used for the training.

III. RESULTS

In this section, the experimental results for the validation of the proposed method were illustrated including the 3D distance errors in the marker prediction, the 2D projected and 3D distance error in the marker instantiation, as well as the angular and the mesh error in the stent segment instantiation.

A. Prediction of 3D Marker References

Figure 5(a) shows an example of training and validation loss curve with around 120 k iteration steps. The mean 3D distance between the predicted 3D marker references by the adapted GCN and the ground truth, called A-GCN, that for ANN, and the initial mean 3D distance between the 3D fully-deployed markers and the ground truth, named initial variation, for the 26 partially-deployed stent segments are shown in Figure 5(b). We can see that the mean 3D distance achieved by the adapted GCN is lower than the initial variation and the ANN with \( p = 3.2 \times 10^{-4} \) and \( 3.9 \times 10^{-4} \) using one-sided hypothesis rank-sum tests respectively, proving the efficiency of the proposed adapted GCN on 3D marker reference prediction. The mean 3D distances achieved by the adapted GCN for the iliac stent graft (stent segment number from 1 to 8) are comparable to the initial variations. Because the diameter of the iliac stent graft is very close to that of the deployment catheter (due to limited experimental resources, we only got one available deployment catheter), and there is no much difference between the fully-deployed and partially-deployed state of the iliac stent graft.

B. 3D Marker Instantiation

The predicted 3D marker position references and the manually detected 2D marker references for partially-deployed stent segment are imported into the shape instantiation framework [8] to recover the intra-operative 3D marker positions. The instantiated intra-operative 3D marker positions and their 2D projections are compared to the corresponding ground truths, with examples shown in Figure 6. We can see that the instantiated marker positions are very close to the ground truth in both 3D and 2D. Due to the imaging error caused by the fluoroscopic system, [0.5, 0.8] mm deviation exists between the manually detected
Fig. 6. (a) Comparison of instantiated intra-operative 3D marker positions and the 3D ground truth, and (b) comparison of 2D projections of instantiated 3D markers and the 2D ground truth for the adapted GCN.

Fig. 7. Mean±std 3D (a) and 2D re-projected (b) distance errors of the instantiated intra-operative marker positions for the adapted GCN (A-GCN) with the ideal (green) and practical (blue) 2D marker position as the input 2D reference, and for the ANN with practical 2D reference (purple), compared with the Non-deformed instantiation using fully-deployed stent as the 3D reference (red).

2D marker position reference, named practical 2D marker reference, and the projected 2D marker position reference from the ground truth 3D marker position reference, named ideal 2D marker reference. Both of these two 2D marker references are used with the predicted 3D marker reference to instantiate the intra-operative 3D marker positions. The 3D and 2D re-projected distance errors for the 26 partially-deployed stent segments are shown in Figure 7. We can see that an average 2D distance error of 1.58 mm and an average 3D distance error of 1.98 mm are achieved by the adapted GCN respectively. The outliers of 2D distance errors up to 9 mm are mainly caused by the accumulated error from the prediction of 3D references. Using one-sided hypothesis rank-sum tests, 2D and 3D distance error based on the adapted GCN are smaller than the baseline with $p = 4.0\%$ and $5.1 \times 10^{-4}$, as well as the ANN with $1.4 \times 10^{-3}$ and $2.1 \times 10^{-4}$. A two-sided rank-sum test between using practical and ideal 2D marker reference based on adapted GCN with $p = 0.92$ and 0.95 in 2D and 3D indicates that the robustness of the instantiation framework to the imaging error introduced by the fluoroscopic system.

C. Shape Instantiation of Partially-Deployed Stent Segment

As the graft could not be imaged via CT, the ground truth of a partially-deployed stent segment was estimated by registering the mathematical model in Sec. II-A onto the ground truth 3D marker reference. Two comparison examples of the instantiated partially-deployed stent segment and the estimated ground truth are shown in Figure 8. Two comparison examples of the instantiated partially-deployed stent segment and the real ground truth represented by the CT stent scan are shown in Figure 9. We can see that reasonable 3D shape instantiation is achieved.

The mean angular error between the instantiated intra-operative 3D markers and the ground truth is shown in Figure 10(a). The mean angular errors achieved by adapted GCN are smaller than the baseline and ANN with $p = 3.9\%$ and $6.7 \times 10^{-3}$ in one-sided rank-sum tests but the average angular error around $7^\circ$ is larger than the average angular error of $4^\circ$ in [8]. This is reasonable, as the 3D marker references for
partially-deployed stent segments are unknown and the prediction process causes errors. The mean angular error for iliac stent graft (stent segment number 1 to 8) is larger than that for the fenestrated and thoracic stent graft (stent segment number 9 to 26) due to the same reason stated in Sec. III-A. The mean distance errors between the instantiated stent segment meshes and the ground truths are shown in Figure 10(b). A one-sided rank-sum test indicates that adapted GCN achieved smaller mesh distance error than the baseline and the ANN with $p = 9.8 \times 10^{-5}$ and 4.5% in one-sided rank-sum tests. An average distance error of [1.0, 2.4] mm is achieved which is comparable to the average distance error in [8]. The iliac stent graft experiences lower mean distance error than the fenestrated and thoracic stent graft, as its size is smaller. The 2D and 3D distance errors for marker instantiation of the stent segment 15 are up to 9 and 7 mm but the corresponding mesh distance errors and angular errors are up to 3 mm and $9^\circ$, showing the robustness to outlier values.

Furthermore, the 3D distance error for the 3D marker prediction, the 2D projected and 3D distance error for the intraoperative 3D marker instantiation, the angular and distance error for the 3D shape instantiation of partially-deployed stent segments in each experiment are shown in Table I.

For instantiating each stent segment on a computer with a CPU of Intel Core(TM) i7-4790 @3.60 GHz × 8, the computational time is around 7 ms using Matlab. The 3D marker reference prediction in Tensorflow on a Nvidia Titan Xp GPU costs around 0.8ms for each stent segment. The training of the adapted GCN takes around 5 hours. The implemented code was written based on the work of [13].

IV. DISCUSSION

In this letter, a 3D shape instantiation approach based on a previously deployed framework [8] is proposed for partially-deployed stent segment from a single intra-operative 2D fluoroscopic image. It is validated on three commonly used stent grafts with five different AAA phantoms. The mean distance errors of the instantiated partially-deployed stent segments are from 1.0 to 2.4 mm and the mean angular errors of instantiated markers are around from $5^\circ$ to $11^\circ$.

Without knowing pre-operative 3D marker references, the adapted GCN is introduced and achieves reasonable 3D marker reference prediction (an average 3D distance error of 1.5 mm for the fenestrated and thoracic stent graft) from 3D fully-deployed markers. However, the 3D marker reference prediction for the iliac stent graft is insufficient. The diameter of the deployment catheter used in the experiments is almost the same as that of the iliac stent graft, resulting in the partially-deployed 3D marker set shape is almost the same as the fully-deployed one. In the cross validation for the iliac stent graft, the adapted GCN was trained on the fenestrated and thoracic stent graft data for learning partially-deployed deformation. The trained model would not be suitable for predicting 3D marker references for the iliac stent graft which did not experience obvious partially-deployed deformation.

In the training of the adapted GCN, batch normalization and dropout were also explored, but these two methods decreased the accuracy. One potential reason for batch normalization performance is that the network for regression tasks is sensitive to the scale of feature values, but batch normalization changes them. For dropout performance, there is no saturation area in the output function without softmax function, and thus the randomly dropped neurons in the training phase affect the testing results. Future work is essential to confirm the feasibility of batch normalization and dropout in the proposed adapted GCN.

The errors of 3D marker or shape instantiation with using ideal and practical 2D marker references are very similar in Figure 7 and Figure 10, implying that the proposed framework is insensitive to the imaging errors caused by the fluoroscopic system. Instantiating partially-deployed stent segment includes mainly three steps: marker segmentation which costs 0.1 s on an Nvidia Titan Xp GPU [9], 3D marker reference prediction which costs 0.8 ms, and 3D shape instantiation which costs 7 ms. The total computational time is less than 0.11 s, which potentially could achieve real-time running as the typical frame rate for clinical usage is around 2 to 5 frames per second.

The proposed method, as a step forward to obtain the real-time 3D shape instantiation for stent grafts, could be potentially used in FEVAR navigation. In the future, this letter could be combined with the 3D shape instantiation for fully-deployed [8] and fully-compressed [7] stent segment to build a system of real-time 3D shape instantiation for stent grafts at any states.
The Equally-weighted Focal U-Net [9] could be integrated into the framework for improving the automation.

V. CONCLUSIONS

A 3D shape instantiation framework for partially-deployed stent segment was proposed in this letter, including stent segment modelling, 3D marker reference prediction, marker instantiation and shape instantiation. Only one fluoroscopic image with minimal radiation is required as the intra-operative input. The adapted GCN is introduced to explore the variation pattern of 3D markers and to provide the 3D marker references for 3D marker instantiation. Compared with the previous relevant work, the proposed framework focuses on dealing with the difficulties of predicting the stent segment shape at the partially-deployed state and achieved a comparable accuracy.

ACKNOWLEDGMENT

The authors would like to thank NVIDIA Corporation for the donation of the Titan Xp GPU used for this research.

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