A deep learning model for positioning perforated stent

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Abstract. How to determine the window position of the aortic stent is an important issue in cardiovascular disease research. Currently, this process is viewed in two dimensions, and a lack of information is prone to errors. Here, the real-time frame is suggested to enumerate the three-dimensional shape using the two-dimensional perspective image. A robot-assisted window-opening stent implantation with deep learning is geometrically aligned ratios in window-opening aortic endovascular repair. First, place markers during the windowed stent. Then, we located the three-dimensional pose of each stent segment. Third, the overall three-dimensional shaped stent-graft is achieved by graft gap in terpolation. It has been proposed to separate the markers from the two-dimensional fluorescence microscope for semi-automatic label detection of the image. In this way, we can better understand the opening position of the aortic stent.

1. Introduction
The aortic stent consists of the tubular wire mesh, inserting a narrow artery and applying a thin layer of some medicines to prevent immune rejection with the human body. Stents depend on many factors, such as physical and geometric factors [1], coating parameters and biochemical characteristics of blood vessels. All of these play significant roles in the human body. Different stents have different implantation locations [2]. The degree of vascular curvature also affects the placement of stents [3]. Implanting stents in highly curved arteries has always been a big challenge [4], and also has an important impact on the material diffusion of the vascular wall. It is a complex process that some vortices are generated after stenting in some aneurysmal sites. The physical process also has a direct impact on the deformation of blood vessels and stents. This process also affects the flow of blood and the diffusion of molecular substances in blood vessels. Therefore, stent implantation has an impact on the vascular wall, such as endothelium, intima, and internal elastic layer, which will change the previous material transport and diffusion process.

Inspired by the investigations mentioned, we used robotic-assisted fenestration stent implantation to achieve ratio geometric alignment in fenestrated aortic endovascular repair by using Robust Perspective-n-Point (RPnP) method. Two-dimensional perspective is used to analyze the impact of information shortage and error-prone with deep learnig.

2. Structure of the stent graft
The abdominal aortic aneurysm (AAA) is inserted through the femoral artery into a compressed stent-graft, through the development of the vasculature, and subsequent equipment deposits and excludes the aneurysm wall. As we can see in Fig. 1, under fluoroscopy, the visibility of the stent and graft is
poor. High-dose fluoroscopy can improve visualization, which used to increase the radiation dose. The tracking of stent-graft transport has been proposed with devices obtained from 2D perspective images [5].

![Figure 1. Different conditions of EVAR [5]](image)

### 3. Mathematical model and methods
We discuss the main contents of stent-assisted detection, including modeling of stent-grafts, instantiation of 3D stent-graft shapes and marking positions.

#### 3.1. Stent graft model
Previous work [6] on vascular stent research usually focused only on modeling the composition of the stent, and only considered the situation of the two-dimensional vascular stent. Here, we define the circle vertex as \([r \cos \alpha, r \sin \alpha, h]\). Moreover, \([r \cos(2\pi N_v \alpha), r \sin(2\pi N_v \alpha), h' \sin(2\pi N_s / N_v)/2]\) is applied to simulate the mathematical model of stent graft [7], in which \(N_v\) refer to the vertex number, \(N_s\) is defined as the number, \(h'\) is introduced to the height.

#### 3.2. 3D stent segment model
The bracket segment can be instantiated by its three-dimensional pose of \(n\) mark using RPnP method.

1) Marker placement: The location pattern of each support segment is similarly used for the latter tag classification.

2) 3D Pose Instantiation for Stent Segment: To better instantiate the pose of the bracket segment, we analyze the specific process of the bracket modeling in detail [8]. Step 1, because there are many unknowns in the solution process, we choose the \(Z\) axis as the rotation axis to calculate the solution process simply. Step 2, our solution to the stent can be reduced to a complex system of equations

\[
f_i(x) = p_i x^4 + q_i x^3 + r_i x^2 + s_i x + t_i = 0, \quad i \in (1, n-2),
\]

where

\[
p_i = M_i^2 - M_i M_s^2,
q_i = 2 \left( M_i^2 M_o - M_i M_s M_s \right),
\]

\[
dr_i = M_i^2 + 2 M_s M_i - M_i s_i^2 - M_s M_s,
\]

\[
t_i = 2 \left( M_i M_i - M_i M_i M_i \right),
\]

\[
e_i = M_i^2 - M_s M_s,
\]

in which \(M_i (i = 1, \ldots, 7)\) is as follows,

\[
M_1 = \lambda^2,
\]
Here, $\lambda = N_2 / N_1$, $N_1, N_2, N_3$ are the triangle side lengths, $|p_0 p_1|, |p_0 p_2|, |p_1 p_2|, C_1, C_2, \mu_0, \mu_1, \mu_2$ denote in [9]. Step 3, we use the geometric method of perspective similar triangle to solve each mark of stent graft. Step 4, during the mathematical model, the rotation $c = \cos \beta$, $s = \sin \beta$ with the Z axis and its translation $[t_x, t_y, t_z]$ of the markers are computed through [8]:

$$
[M_{2n \times 2} B_{2n \times 4}] \begin{bmatrix} \cos t_x \cos t_y \cos t_z \end{bmatrix}^T = 0
$$

(4)

The process of $M_{2n \times 2}$ and $B_{2n \times 4}$ can be found in [8]. Step 5, we use the Least-Squares Estimation [10] to solve the transformation matrix with the normalized standard 3D alignment form.

3.3. 3D stent graft instantiation

The grafting gap vertex of this interpolation is calculated by the following formula:

$$
\begin{bmatrix}
x'_i \\
y'_i \\
z'_i
\end{bmatrix} = \begin{bmatrix} r_{c_{\alpha+T}, r_{s_{\alpha+T}, 0}} & x_i \\
y_i \\
z_i
\end{bmatrix} + \begin{bmatrix}
c_{\Pi} + \beta^2 c_{\Pi r} \\
\beta \phi c_{\Pi r} - \delta s_{\Pi r} \\
\beta \delta c_{\Pi r} - \phi s_{\Pi r}
\end{bmatrix} + \begin{bmatrix}
c_{\Pi r} + \phi^2 c_{\Pi r} \\
\phi \delta c_{\Pi r} + \beta s_{\Pi r} \\
c_{\Pi r} + \delta^2 c_{\Pi r}
\end{bmatrix},
$$

(5)

(6)

where $\alpha \in (1 \circ .360 \circ)$ refers to the angle, $r_i$ denotes the radius, $c_\Pi = 1 - c_\Pi$. Here, $c_\alpha+T$ refers to $\cos(\alpha + T)$ and $c_\Pi$ refers to $\cos(\Pi)$. $s_\alpha+T$ represents $\sin(\alpha + T)$ and $S_\Pi$ is introduced for $\sin(\Pi)$.

3.4. Deep learning with stent graft

All convolution layers are zero-filled, with a step of 1 and Step 2 for all maximum pool levels. For binary splits, we have

$$
\text{loss}_{\text{cross-entropy}}(\xi, \omega) = \begin{cases} -\log(\xi), & \omega = 1 \\ -\log(1-\xi), & \omega = 0 \end{cases},
$$

(7)

where $\xi \in [0,1]$, which is the probability. $\omega = 0$ is as the background, $\omega = 1$ is as the foreground. Equation (7) could be rewritten as loss crossentropy $(\xi_\omega) = \text{loss crossentropy} (\xi_t) = \log(\xi_t)$, where

$$
\xi_t = \begin{cases} p, & \omega = 1 \\ 1 - p, & \omega = 0 \end{cases}.
$$

(8)

In our case, the ground marker and background of the two classes is very unbalanced. However, its performance on the issue of extreme class imbalance. Therefore, focal length loss is applied in this work [29]:

$$
\text{loss}_{\text{focal}}(\xi_t) = -\chi_\omega (1 - \xi_t)\gamma \log(\xi_t),
$$

(9)

in which $\gamma$ is the power factor. In our experiment, $\chi_\omega$ is set to 30 and $\gamma$ is set to as suggested by [11]. To some extent, the group’s overweighted loss will be proved instead of distributing a constant weight to the front wing.
4. Results and discussion
We consider the 3D shape instantiation of stent scaffold. The displacement corrected by calibration at the center, as shown in Fig. 2. The angle error is the instantiation mark and the basic fact of the unsigned angle. Measuring angle error, such as the direction of the opening window or scallop, is very important for robot-aided path planning.

![Figure 2. Physiological structure of vascular wall](image)

In our analysis, the contact is not strict, and the graft deformation is divided into the rigid transformation of segmented scaffold segments and then instantiation by inserting these instantiated scaffolds. It shows that this split is reasonable and can be used for further study of stent transplantation. Stents, 3D printed aneurysms, stents all appear in the two-dimensional fluorescent images of our, mathematical model. We consider and propose focus U-net, which realizes the research progress of image marker-free segmentation and preprocessing, compared with weighted U-net. The background of small segmentation will be greatly reduced. In this work, the manual classification of tags as tag shapes is not well designed to be different shapes. The precision of 3D shape instancing based on semi-automatic marking is similar to that of manual marking. However, there is no overlapping of tags, so tag classification is easier and still tends to avoid tag misclassification.

5. Conclusions
In this paper, we analyze the relevant knowledge of the windowed stent using machine learning, Least-Squares Estimation method, Robust Perspective-n-Point (RnP), and other related knowledge. Compared with the latest 2D model, in our mathematical model, the proposed 3D model can instantiate with the shape of the stent, grafts, windows, and scallops. Future work should therefore include that the shape of the mark optimize the design for the stent.

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