Trajectory planning for robot-assisted laminectomy decompression based on CT images

Qian Li¹, Zhijiang Du¹ and Hongjian Yu¹,*
¹State Key Laboratory of Robotics and System, Harbin Institute of Technology, Harbin, China
*Corresponding author e-mail: yuhongjian99@126.com

Abstract. Laminectomy decompression is one of the most complex spinal operations, with a high surgical risk and surgeon fatigue. The introduction of robots into surgery is expected to effectively solve these problems, but the complex and time-consuming grinding planning hinders the research and application of robot-assisted laminectomy. This paper proposes a robot grinding path automatic generation method for this operation to simplify the planning process. First, a neural network is designed to obtain the central positions of laminae in a CT image. Around the laminar center, a series of sparse robotic motion control points are obtained and adjusted based on bone surface. Simulation experiments based on some spine CT datasets indicate that the proposed method can effectively generate a reasonable planned path from spine CT images.

1. Introduction
Lamina decompression is one of the most effective surgical methods for the treatment of lumbar spinal stenosis (LSS) [1]. The purpose is to remove the lamina above the spinal nerve to relieve its stress which will cause the patient a lot of pain. Today, as people's lifestyles change, more and more people are diagnosed with spinal stenosis [2]. In a traditional laminectomy, with the help of CT images, the surgeon uses a medical grinding drill to grind the laminae in the open field of view. Usually, they will remain some bone unground for subsequent operations. However, due to the lack of a precise grinding trajectory, surgeons may wear through the entire lamina and injure the nerves by mistake, which will lead to serious complications, and patients may suffer long-term pain or even death [3].

Due to the gradual maturity of robot technology and the development of computer-assisted medical treatment, great progress has been made in the field of robot-assisted surgery, such as robotic cochlear implantation [4] and robotic pedicle screw placement [5]. Compared with a surgeon, the robot has the characteristics of high precision and high stability, and does not feel tired, and can be easily copied [6]. However, because of the limitation of technology, the current robots cannot yet possess the human-like visual ability, and thus cannot rely on visual feedback to operate during surgery. Therefore, an image-based trajectory planning before surgery is vitally important.

In fact, many researchers have noticed the important role of automatic path planning in robot-assisted surgery. For example, Zhang, Li [7] realized path planning in an anterior spinal surgery using reinforcement learning and a tool path generator for minimally invasive orthopedic surgery was designed in [8] and [9]. For laminectomy decompression, a semi-automatic planning method was proposed in [10]. In this method, 48 trajectory control points can be calculated automatically based on the CT image, but surgeons need to select the grinding position, path direction, and grinding region in
a 3D model in advance. Although this method simplifies the operation of the doctor to some extent, it still requires the doctor to specify some information that has already existed in the image.

2. Method

In a robot-assisted laminectomy, careful planning movement position of the instrument is necessary because it will affect the grinding process and the remaining grinding amount. Due to the requirements of the grinding task, a series of control points need to be specified. Given the spherical grinding tool, we will give the planned position of the spherical center here for the convenience of calculation. The process of automatically generating control points includes three steps, which are to generate the lamina center position, the first and last layer points, and the middle layers points.

2.1. Laminar central position generation

A lamina is an anatomical structure on the vertebral body and there are two on each vertebral body. Given the size of the CT image during the procedure, 6 to 8 laminae may appear in each CT image. The task is to identify all laminae from the image and locate them.

Recently, deep learning has achieved many promising results in spine CT image processing, including spinal segmentation [11] and localization [12]. Therefore, we designed a laminar positioning network (LPN) shown in Figure 1 based on DenseSeg Net [13]. Inspired by [12], the trained network outputs a Gauss Mixture Probability Map (GMPM) to estimate the laminar centers.

In an intraoperative spinal CT image, the number of laminae is indeterminate because of different spine postures. Therefore, we use the DBscan algorithm [14] to obtain the coordinates of each laminar center from the GMPM (Figure 2). Specifically, we extract the coordinates of points with probability greater than 0.5 in the map, and use the probability values at these points as their weights. By DBscan, these coordinates are separated according to different lamina. Finally, a weighted average operation is used on them to generate the coordinates of each laminar center. Finally, the spinal direction $S = [s_x, s_y, s_z]^T$ is derived from these laminar coordinates.

2.2. Control points of the first and last layers

After designating the lamina to be ground, a series of grinding control points will be generated around the obtained laminar center to control the motion of the robot. Usually, the robot will be commanded to mill the bone layer by layer from the outer surface to the inner surface of the lamina based on these points. In this process, the grinding trajectories of the first and last layers should be determined according to the topography of the outer and inner surfaces of the lamina, respectively.
Specifically, a plane passing through the center of the lamina $[X_0, Y_0, Z_0]^T$ and inclined by an angle $\theta$ about $S$ is generated (Figure 3). In the following, point generation method in this plane coordinate system will be discussed, and the final trajectory control points will be obtained by the transformation from the 2D coordinate system $[x, y]^T$ to the 3D image coordinate system $[X, Y, Z]^T$.

![Figure 2. Laminar centers generation from a GMPM. The obtained points are shown by the blue marks.](image)

![Figure 3. Automatic generation of the planning plane. The red spheres denote the estimated laminar centers. The planning plane (the black one) is obtained by rotating the vertical plane (the green one) about $S$. Similar to [10, 15], some bone surface points on this plane are sampled uniformly along the spinal direction (Figure 4). Because of the intervertebral foramen, those extra points are able to be eliminated. In some special cases, the shape of the lamina may cause a sudden drop of the control point, which will have a negative impact on subsequent work. Considering the size of the grinding burr, the points at the boundary are removed because the bone in these areas would be ground away when the instrument moves to other points.](image)

![Figure 4. An example of control points.](image)
The actual trajectory control points are adjusted according to these points. Points of the first layer are adjusted based on the radius \( R \) of the burr and the initial grinding depth \( D^i \) and points of the last (\( l^{th} \)) layer are adjusted based on \( R \) and the remained safety distance \( D_{safe} \).

\[
\begin{align*}
\begin{bmatrix} x_j^i \\ y_j^i \end{bmatrix} &= \begin{bmatrix} x_j^0 \\ y_j^0 \end{bmatrix} + \left( R - D^i \right) \mathbf{n}_j^0, \quad j = 1, 2, \ldots, m \\
\begin{bmatrix} x_j^{l+1} \\ y_j^{l+1} \end{bmatrix} &= \begin{bmatrix} x_j^{l+1} \\ y_j^{l+1} \end{bmatrix} + \left( R + D_{safe} \right) \mathbf{n}_j^{l+1}, \quad j = 1, 2, \ldots, m
\end{align*}
\]

Where \( \begin{bmatrix} x_j^i, y_j^i \end{bmatrix}^T \) denotes the \( j^{th} \) control point of the \( i^{th} \) layer and particularly it denotes the outer or inner surface points when \( i = 0 \) or \( i = l + 1 \). Besides, \( \mathbf{n}_j^0 \) and \( \mathbf{n}_j^{l+1} \) denote the surface normal vector (NV) at the \( j^{th} \) point of the outer surface and inner surface respectively. In order to simplify the computational complexity and avoid excessive robot movement caused by the non-smooth bone surface, we use the sparse points \( \begin{bmatrix} x_j^0, y_j^0 \end{bmatrix}^T \) and \( \begin{bmatrix} x_j^{l+1}, y_j^{l+1} \end{bmatrix}^T \) to compute the value.

\[
\mathbf{n}_j^i = \begin{cases} 
\mathbf{N} \left( -\frac{y_j^0 - y_j^i}{x_j^0 - x_j^i}, 1 \right) & j = 1 \\
\mathbf{N} \left( -\frac{d_j^j y_j^{i+1} - y_j^j}{d_j^j x_j^{i+1} - x_j^j}, \frac{d_j^j y_j^{i+1} - y_j^j}{d_j^j x_j^{i+1} - x_j^j}, 1 \right) & j = 2, 3, \ldots, m - 1, \quad i = 0, l + 1 \\
\mathbf{N} \left( -\frac{y_{j+m}^j - y_{l+1}^j}{x_{j+m}^j - x_{l+1}^j}, 1 \right) & j = m
\end{cases}
\]

Where \( d_j^j \) is the distance and \( \mathbf{N}(\cdot) \) is the normalized function.

\[
d_j^j = \sqrt{\left(x_j^{i+1} - x_j^j\right)^2 + \left(y_j^{i+1} - y_j^j\right)^2}, \quad j = 1, 2, \ldots, m
\]

\[
\mathbf{N}(a, b) = \left[ \frac{a}{\sqrt{a^2 + b^2}}, \frac{b}{\sqrt{a^2 + b^2}} \right]^T
\]

### 2.3. Control points of middle layers

For grinding tasks, the middle layers’ points are not that important compared to other points, so they can be obtained simply by linear interpolation [10, 15]. Prior to this, however, it is necessary to determine the number of grinding layers by the grinding thickness. After generating all points of the first and last layers, the maximum grinding thickness can be calculated.

\[
T_{\text{max}} = \max_{j \in \text{even}} \sqrt{\left(x_j^l - x_j^i\right)^2 + \left(y_j^l - y_j^i\right)^2}
\]

Thus the number of grinding layers is

\[
l = \text{ceil} \left( \frac{T_{\text{max}}}{D} \right) + 1
\]

Where \( \text{ceil}(\cdot) \) denotes the round-up operation and \( D \) denotes the allowable maximum grinding depth. Therefore, the points of the middle layers can be expressed as

\[
\begin{align*}
\begin{bmatrix} x_j^i \\ y_j^i \end{bmatrix} &= \frac{l - i}{l - 1} \begin{bmatrix} x_j^i \\ y_j^i \end{bmatrix} + \frac{i - 1}{l - 1} \begin{bmatrix} x_j^{l+1} \\ y_j^{l+1} \end{bmatrix}, \quad i = 2, 3, \ldots, l - 1; \quad j = 1, 2, \ldots, m
\end{align*}
\]

It is worth noting that the mark \( j \) does not represent the grinding order because the grinding order on the even layers is the opposite.
3. Experiments and results

3.1. Experimental settings

In order to verify the feasibility of the proposed algorithm, we conducted experiments with publicly available datasets on the network, including Lumbar vertebra segmentation CT image datasets (LumSeg)[16, 17], Spine and Vertebrae Segmentation datasets (SpiSeg)[18], and xVertSeg datasets (xVertSeg)[19]. We manually labeled the position of the lamina in these images. Maps with several Gauss distribution centered on these positions was used as the GT for training the LPN. An example of these datasets is shown in Figure 5.

![Figure 5. The publicly available datasets. We show the CT image slices (up) and the GT slices (down) here. (From left to right, LumSeg, SpiSeg and xVertSeg)](image)

The LPN model was implemented and trained with the PyTorch framework on a desktop with a NVIDIA GTX 2080 Ti graphics card. And QT was used to realize other planning functions and interactive interfaces.

3.2. Experimental Results

A 10-fold cross-validation was used to train and validate the LPN. As shown in Table 1, the average positioning error for laminar centers is 2.373 ± 0.974mm. However, the main part of errors is those in Z direction which will have little impact on the planning results. Besides, since the definition of the laminar center is not very precise, different experts will give different labeling results. This means that such positioning results are allowed and the effectiveness were proved by subsequent experiments.

![Table 1. The positioning error of LPN. The data are shown as mean ± standard error.](table)

Through a similar method in [10], a segmented image containing the bone tissue in the CT image and its 3D reconstruction model were obtained. Using the lamina center output by the LPN and the method described above, a series of planning control points were generated. Some examples of grinding planning control points are shown in Figure 6. These control points cover most of the pixels in the area to be ground, and a bone of equal thickness on the inner surface is retained to prevent over-grinding.
4. Discussion and conclusion

This paper proposes a method for the automatic generation of grinding trajectories for robot-assisted laminar decompression. A neural network processing spinal CT images is designed to output a GMPM that represents the laminar center position probability. Around the center of the lamina to be ground, some points are generated based on the upper and lower surfaces of the lamina to control the robotic trajectory. In the experiments, the neural network LPN used to locate the center of the lamina achieved an average error of 2.373 mm. These positioning errors were counted in each direction to analyze. The results show that the error in the left-right direction of the patient which affects subsequent planning is only 1.124 mm, which can be considered to meet the needs of surgery. Some examples of planning control points are given, where we show the generation of control points and the deletion of other points.

5. Acknowledgments

This work was financially supported in part by National Natural Science Foundation of China (U1813213 and 61673139).

References

[1] Ghogawala, Z., et al., Laminectomy plus Fusion versus Laminectomy Alone for Lumbar Spondylolisthesis. N Engl J Med, 2016. 374(15): p. 1424-34.
[2] Atlas, S.J. and A. Delitto, Spinal stenosis: surgical versus nonsurgical treatment. Clin Orthop Relat Res, 2006. 443: p. 198-207.
[3] Stromqvist, F., et al., Incidental durotomy in degenerative lumbar spine surgery - a register study of 64,431 operations. Spine J, 2019. 19(4): p. 624-630.
[4] Weber, S., et al., Instrument flight to the inner ear. Science Robotics, 2017. 2(4).
[5] Lonjon, N., et al., Robot-assisted spine surgery: feasibility study through a prospective case-matched analysis. Eur Spine J, 2016. 25(3): p. 947-55.
[6] Chen, Y., et al., Robotic System for MRI-guided Focal Laser Ablation in the Prostate. IEEE ASME Trans Mechatron, 2017. 22(1): p. 107-114.
[7] Zhang, Q., et al. 3D Path Planning for Anterior Spinal Surgery Based on CT images and Reinforcement Learning. in 2018 IEEE International Conference on Cyborg and Bionic Systems (CBS). 2018. IEEE.
[8] Sugita, N., et al., Tool Path Generator for Bone Machining in Minimally Invasive Orthopedic Surgery. IEEE/ASME Transactions on Mechatronics, 2010. 15(3): p. 471-479.
[9] Sugita, N., et al., Toolpath strategy based on geometric model for multi-axis medical machine tool. CIRP Annals, 2011. 60(1): p. 419-424.
[10] YU SUN, Z.J., XIAOZHI QI , YING HU,BING LI, JIANWEI ZHANG, Robot-Assisted Decompressive Laminectomy Planning Based on 3D Medical Image. IEEE Access.
[11] Lessmann, N., et al., Iterative fully convolutional neural networks for automatic vertebra segmentation and identification. Med Image Anal, 2019. 53: p. 142-155.
[12] Yang, D., et al., Automatic Vertebra Labeling in Large-Scale 3D CT using Deep Image-to-Image Network with Message Passing and Sparsity Regularization. 2018.
[13] Bui, T.D., J. Shin, and T.J.a.p.a. Moon, 3D densely convolutional networks for volumetric segmentation. 2017.
[14] Ester, M., et al. A density-based algorithm for discovering clusters in large spatial databases with noise. in Kdd. 1996.
[15] Qi, X., et al., Multilevel Fuzzy Control Based on Force Information in Robot-Assisted Decompressive Laminectomy. Adv Exp Med Biol, 2018. 1093: p. 263-279.
[16] Korez, R., et al., A Framework for Automated Spine and Vertebrae Interpolation-Based Detection and Model-Based Segmentation. IEEE Trans Med Imaging, 2015. 34(8)
[17] Ibragimov, B., et al., Shape representation for efficient landmark-based segmentation in 3-d. IEEE Trans Med Imaging, 2014. 33(4): p. 861-74.
[18] Yao, J., et al., A multi-center milestone study of clinical vertebral CT segmentation. Comput Med Imaging Graph, 2016. 49: p. 16-28.
[19] Ibragimov, B., et al., Segmentation of Pathological Structures by Landmark-Assisted Deformable Models. IEEE Trans Med Imaging, 2017. 36(7): p. 1457-1469.