

ORIGINAL ARTICLE

Artificial intelligence-based technology to make a three-dimensional pelvic model for preoperative simulation of rectal cancer surgery using MRI

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Abstract

Aim: A new technique that allows visualization of whole pelvic organs with high accuracy and usability is needed for preoperative simulation in advanced rectal cancer surgery. In this study, we developed an automated algorithm to create a three-dimensional (3D) model from pelvic MRI using artificial intelligence (AI) technology.

Methods: This study included a total of 143 patients who underwent 3D MRI in a preoperative examination for rectal cancer. The training dataset included 133 patients, in which ground truth labels were created for pelvic vessels, nerves, and bone. A 3D variant of U-net was used for the network architecture. Ten patients who underwent lateral lymph node dissection were used as a validation dataset. The correctness of the vascular labelling was assessed for pelvic vessels and the Dice similarity coefficients calculated for pelvic bone.

Results: An automatic segmentation algorithm that extracts the artery, vein, nerve, and pelvic bone was developed, automatically producing a 3D image of the entire pelvis. The total time needed for segmentation was 133 seconds. The success rate of the AI-based segmentation was 100% for the common and external iliac vessels, but the rates for the vesical vein (75%), superior gluteal vein (60%), or accessory obturator vein (63%) were suboptimal. Regarding pelvic bone, the average Dice similarity coefficient between manual and automatic segmentation was 0.97 (standard deviation 0.0043).

Conclusion: Though there is room to improve the segmentation accuracy, the algorithm developed in this study can be utilized for surgical simulation in the treatment of advanced rectal cancer.

KEYWORDS

artificial intelligence, deep learning, magnetic resonance imaging, rectal neoplasms, three-dimensional image

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1 | INTRODUCTION

The pelvic cavity contains various organs, including the rectum and urogenital organs, as well as nerves and vessels inside its periphery wall formed by bone and muscles, resulting in highly complicated configurations. Furthermore, these structures, especially vessels, are associated with abundant anatomical variations.^{1,2,3,4} We need to comprehend these complexities during surgery for locally advanced rectal cancers, especially technically demanding surgery including lateral lymph node dissection (LLND) or total pelvic exenteration, not only rectal resections, because they are a difficult hurdle for surgeons to overcome.

To address these problems, previous studies have used CT-based three-dimensional (3D) images of the pelvic anatomy for preoperative simulation.^{5,6,7} In some studies, a 3D printer was utilized to fabricate a solid anatomical model based on the CT-based images.^{6,7} Certainly, a clear view of arteries can be provided by CT when contrast agent is administered, or the 3D shape of the rectum can be visualized using air colonography, but these techniques cannot clearly differentiate veins or nerves, mainly due to the variability or overlap of CT intensity ranges with neighboring anatomical structures. Previous methods to automate 3D modeling from CT have been based on an algorithm to extract the anatomy of interest by analyzing the contrast density; therefore, soft organs, including nerves, cannot be extracted and images of veins tend to get blurred. Moreover, even after automatically detecting vascular structures based on differences in the CT values, we need to process the 3D images to amend the anatomical insufficiencies, creating a heavy workload for medical staff. There is room for improvement in the field of CT-based reconstruction with the aim of preoperative simulation for rectal cancer surgery.

A better way to distinguish individual anatomical structures than CT is to use MRI, which is also a prerequisite exam in the preoperative work-up for rectal cancer.^{8,9} Using the standard protocol for MRI in rectal cancer patients, each slice is too thick to create a 3D model¹⁰; however, if we use 3D MRI, sequential images with thin slices at various angles can be obtained.¹¹ Taking these characteristics of 3D MRI into consideration, it is plausible that MRI would be efficient at creating 3D images for preoperative simulation. Until now, no tools have been available to reconstruct 3D images from MRI for the treatment of rectal cancer, though we considered that recent advancements in artificial intelligence (AI) can realize the automated segmentation differently from the classic methods.^{12,13} In the present study, we attempted to develop an automated algorithm to create a 3D model from pelvic MRI using AI technology, thereby contributing to advancements in preoperative simulation.

2 | METHODS

2.1 | Patients

A total of 143 patients who underwent 3D MRI as a preoperative examination for rectal cancer between December 2018

and November 2021 at our institution were included in this study (Figure 1). The protocol for this research project was approved by the Ethics Committee of Sapporo Medical University. The procedures were carried out in accordance with the provisions of the Declaration of Helsinki of 1995 (as revised in Brazil, 2013).

2.2 | Acquisition of 3D MR images

No bowel preparation or air insufflation was used, though intramuscular antispasmodic agents were routinely used. MR images were acquired using a 3.0-T MR imager (Ingenia; Philips Healthcare, Best, the Netherlands) with a phased-array coil (dStream Torso coil; Philips Healthcare) for signal reception. 3D isotropic T2-weighted fast spin-echo images were acquired according to the following conditions: TR/TE, 1500/200 ms; field of view, 256 mm; matrix, 288 × 288; spatial resolution, 0.89 × 0.89 mm.

2.3 | Automatic segmentation algorithm

Magnetic resonance images from 133 patients were used as a training dataset. We prepared ground truth labels for vessels, nerves, and pelvic bone (109, 123, and 57, respectively). The vessels included common, external, and internal iliac vessels and their branches, and nerves included obturator nerves and the sacral plexus. The lumbosacral trunk was considered part of the sacral plexus. Deep learning-based segmentation models were trained for each organ region, including vessels, nerves, and pelvic bone. A 3D variant of U-net, which is popular for biomedical image segmentation, was used for the network architecture.¹⁴ The Dice-loss was used as the loss function.¹⁵ The extracted vascular regions were divided into arteries and veins using the higher-order graph cuts algorithm.¹⁶ In the graph cuts process, the external iliac artery/vein regions and internal iliac artery/vein regions were set as the seed points and the other vessel regions segmented into artery or vein according to the vessel connectivity.

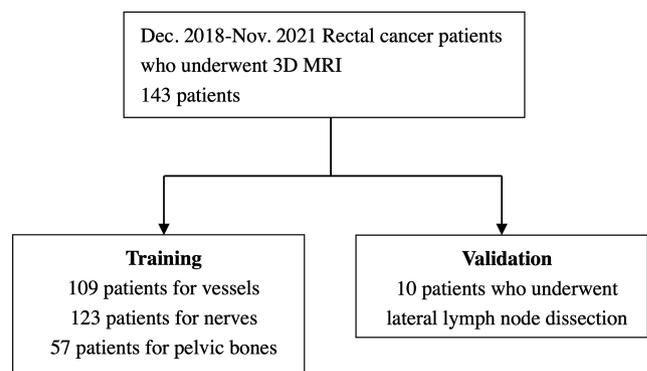


FIGURE 1 CONSORT diagram

2.4 | Validation of the segmentation algorithm

To validate the accuracy of the produced algorithm, 10 patients who underwent LLND for advanced rectal cancer treatment between March and November 2021 were analyzed as a validation dataset. These cases were independent of the cases for which ground truth labels were created. Validation of the vascular and nerve segmentation was carried out according to the previous method used in the assessment of portal and hepatic vein extraction for hepatectomy.¹² Namely, the intrapelvic vessels and nerves were labeled by a colorectal surgeon (AH), and whether these anatomies could be segmented successfully was considered. For cases with variant anatomical type, such as lacking an obturator artery branching from the internal iliac artery, the vessels were not labeled. In assessing the branches of the internal iliac vessels, if the root of the labeled vessel could be segmented successfully, the segmentation of the vessels was defined as being correct, and vice versa. For vesical vessels, several vessels are generally found in many cases; thus, the segmentation was defined as correct if the roots of all vessels were detected. At our institution, we routinely use 3D images of the pelvic artery and veins that were made manually by the dedicated radiological technicians who are not specialized colorectal surgeons using preoperative CT for simulation of LLND, which is not relevant to the current AI-based algorithm. We also analyzed the accuracy of CT-based vascular reconstruction by validating the correctness of the vessels using the same method above. In each case, bilateral pelvic halves were investigated, and a total of 20 halves were eventually analyzed. For the validation for AI-based segmentation of the pelvic bone, we used the Dice similarity coefficients (DSCs) between manual segmentation and automatic segmentation. To assess the usability of the algorithm, the time needed for automated segmentation was calculated on a laptop in which the measurement was performed separately for pelvic bone, vessels, and nerves.

3 | RESULTS

3.1 | Development of AI-based segmentation software

The backgrounds of the patients in the training dataset are provided in Table 1. For development of the algorithm, both early and advanced stage cancer were included because this study focuses on the normal structure of the pelvic anatomy. We developed an automatic segmentation algorithm that extracts the arteries, veins, nerves, and pelvic bone. The algorithm output was a 3D segmentation mask image, thereby automatically producing a 3D image of the entire pelvis (Figure 2A–E). The image provides a visualization of the pelvis from the caudal side, corresponding to the operative field during the transanal/transperineal approach for rectal cancer, as well as the cranial view useful for visualizing the whole pelvis during surgery. For the purpose of allowing surgeons to comprehend the anatomical configuration in the deep pelvis, 3D images of the pelvic

TABLE 1 Characteristics of the analyzed patients

Training dataset		
Age, years	Median (range)	66 (34-90)
Sex, n	Male	85
	Female	48
BMI, kg/m ²	Median (range)	22.7 (13.4-32.6)
Stage, n	0	6
	I	27
	II	58
	III	34
	IV	8
Validation dataset		
Age, years	Median (range)	67 (51-74)
Sex, n	Male	7
	Female	3
BMI, kg/m ²	Median (range)	21.1 (20.2-26.7)
Stage, n	II	6
	III	4

halves can be created bilaterally using software (Figure 2F and G). The time needed for automated segmentation is shown in Table 2. The total time needed for segmentation was 133 seconds, in which vascular segmentation took the longest.

3.2 | Accuracy of the automated segmentation

The backgrounds of the patients in the validation dataset are also provided in Table 1. This analysis included only stage II or III cases in which LLND was indicated. The success rates of the AI-based segmentation and CT-based reconstruction regarding each part of the anatomy are shown in Table 3. Regarding AI-based segmentation, large vessels, including the common, external, and internal iliac vessels, were segmented with high probability (95%–100%), whereas the rate was lower for the inferior gluteal artery (83%), umbilical ligament (85%), vesical vein (75%), superior gluteal vein (60%), and accessory obturator vein (63%). The average \pm standard deviation Dice similarity coefficient between manual and automatic segmentation was 0.97 ± 0.0043 for the pelvic bone. In CT-based reconstruction, the success rates were low for visualizing the vesical arteries (60%) and umbilical ligament (15%), though those in small veins were comparable to corresponding veins in the AI-based segmentation. Regarding the assessment of vesical arteries in CT-based reconstruction, in eight cases judged to be incorrect during validation, only one of the vesical arteries was not depicted in six cases and neither of the arteries was depicted in two cases.

Figure 3 shows representative images from an identical case that underwent LLND for locally advanced rectal cancer, including individual images of the AI-based segmentation and intraoperative anatomy. In this case, two internal iliac veins (IIVs) drain into the common iliac vein, and there is a bridging vein between the two IIVs

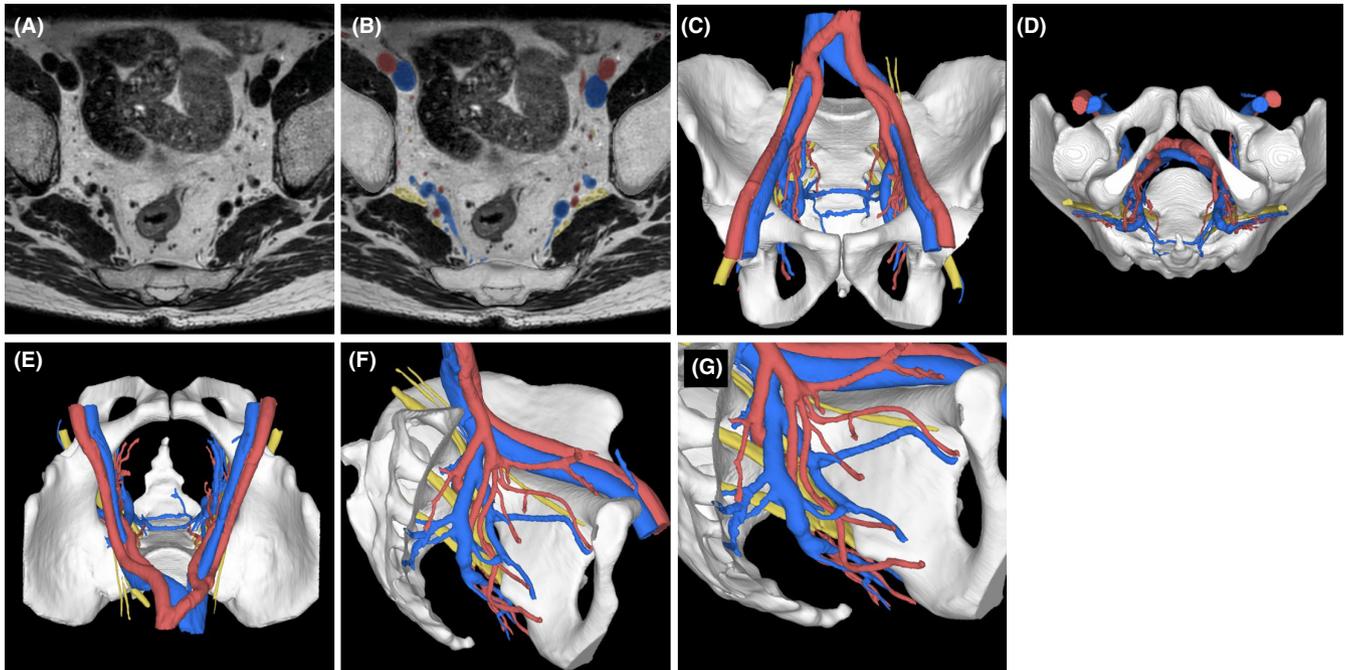


FIGURE 2 Three-dimensional image of the pelvic anatomy created by the artificial intelligence-based algorithm. (A) Axial MRI of the pelvis. (B) Segmentation mask on the axial image. (C) Three-dimensional image of the entire pelvis (frontal view). (D) Three-dimensional image of the entire pelvis (caudal view). (E) Three-dimensional image of the entire pelvis (cranial view). (F) Left-sided pelvic half. (G) Magnified view at the deep pelvis. Red, artery; blue, vein; yellow, nerve; white, bone

TABLE 2 The time needed for automated segmentation

Organ	Time, seconds
Vessels	86.8 (68.1-102.9)
Nerve	20.6 (17.2-22.5)
Bone	25.6 (18.7-29.3)
Total	133.2 (104.0-148.6)

Note: Values are given as median (range).

(Figure 3A and B). Behind the bridging vein, the internal iliac artery runs caudally, and the inferior vesical artery runs in front of this vein. This anomaly could be reproduced on the AI-based algorithm image (Figure 3C).

4 | DISCUSSION

In this study, we developed the first AI-based algorithm to automatically segment the pelvic organs, including vessels, nerves, and bone, from the 3D MRI. This algorithm can be utilized for preoperative simulation of rectal cancer surgery, and potentially for urological or gynecological surgeries. Particularly in difficult cases, such as locally advanced rectal cancer, this algorithm can provide efficient information for the surgeons to comprehend the anatomical configuration preoperatively, which we consider to be related to the implementation of safe and curative surgery. An automated tool for preoperative simulation has not been previously utilized like this in clinical

practice. It is due to the recent progress in AI technology that this kind of algorithm can be developed, and this study is going to take a leading role in this field.

The algorithm has several advantages over previous technologies. The first advantage is that the segmentation data are based on MRI; therefore, we can trace the anatomies that cannot be clearly delineated on CT. The sacral plexus and obturator nerve could be accurately segmented in this study. In the surgeries for advanced rectal cancer, comprehension of the interrelationships between the vessels and sacral plexus is crucial, and this algorithm would play an important role.¹ Regarding the extraction of vessels, the veins are apt to blur on CT-based segmentation because the contrast density in veins cannot reach as high a value as in the artery; thus, the venous contour is forced to be indistinct. However, this algorithm does not depend on the difference in CT values and, therefore, the administration of contrast medium is not required in the acquisition of MRI and this algorithm is not affected by the contrast density. Moreover, a CT-based 3D model is produced by merging the images of vascular structures acquired in the different arterial and venous phases, relating to the risk of organ migration. The anatomical positions of intrapelvic organs may be shifted during the CT examination, with a risk of causing arteriovenous crossover or inversion, but this algorithm is dependent on the one-time MRI, thereby minimizing the risk for organ migration. Considering that, in our analysis, the accuracy of venous segmentation was not superior to that of CT-based reconstruction, the quality of AI-based segmentation must be improved; however, it would be possible to sufficiently increase segmentation accuracy as more training datasets are utilized. One more reason to

	Success rate of automated segmentation	Success rate of CT-based reconstruction
Artery		
Common iliac artery	20/20 (100%)	20/20 (100%)
External iliac artery	20/20 (100%)	20/20 (100%)
Internal iliac artery	19/20 (95%)	20/20 (100%)
Vesical arteries	19/20 (95%)	12/20 (60%)
Obturator artery	16/17 (100%)	16/17 (94%)
Superior gluteal artery	17/20 (94%)	19/20 (95%)
Internal pudendal artery	19/20 (95%)	20/20 (100%)
Inferior gluteal artery	15/18 (83%)	18/18 (100%)
Umbilical ligament	17/20 (85%)	3/20 (15%)
Vein		
Common iliac vein	20/20 (100%)	20/20 (100%)
External iliac vein	20/20 (100%)	20/20 (100%)
Internal iliac vein	20/20 (100%)	20/20 (100%)
Vesical vein	15/20 (75%)	14/20 (79%)
Superior gluteal vein	12/20 (60%)	20/20 (100%)
Obturator vein	13/15 (87%)	11/15 (73%)
Accessory obturator vein	10/16 (63%)	9/16 (56%)
Nerve		
Obturator nerve	20/20 (100%)	NA
Sacral plexus	20/20 (100%)	NA

Abbreviation: NA, not applicable.

use MRI is that we are planning to segment rectal cancer and the surrounding mesorectum together with the pelvic anatomies in the future. MRI can accurately validate tumor-related factors, including the tumor depth or involvement of the mesorectum.^{8,9,17,18} Using the AI-based segmentation algorithm, we may be able to comprehend whole images of the pelvic anatomy in detail, as well as information on tumor extension, thereby utilizing the 3D virtual images for surgical planning in an efficient manner.

Another strength of this algorithm is that the creation of 3D virtual images can be carried out automatically. The time needed for the automated segmentation was approximately 2 minutes. If we intend to create 3D images based on CT using the conventional CT density-dependent method, it would inevitably take far more time and, in the previous studies using a 3D printer, elaboration by the expert surgeons or radiologists and special equipment were mandatory.^{6,7} In another study, a 3D pelvic model was constructed using plastinated slices, but this technology cannot be applied in clinical practice.¹⁹ These restrictions have been hurdles to generalizing these technologies thus far. With this system, we do not need to exert effort in making a 3D model and are able to save costs in fabricating the model. The 3D virtual model can be freely handled on the laptop and can be looked at from any angle, including one similar to the laparoscopic view. The 3D model can be divided according to the operator's intent. For example, the images of the pelvic half shown in [Figure 2](#) can provide in-depth information on the deep

TABLE 3 Accuracy of the automated segmentation

pelvis by being close to the complicated anatomical configuration. Metastasis of advanced rectal cancer to lateral pelvic lymph nodes can frequently occur in this region,²⁰ and comprehending the above anatomical information would be beneficial in surgically eradicating these nodes. Using the caudal pelvic image, we may be able to carry out a preoperative simulation of the transanal or transperineal approach. The good usability will augment the value of this algorithm. Certainly, the accuracy for vascular segmentation has to be ameliorated further, but we are able to correct the image without difficulty on the basis of the current segmentation. This feature curtails the workload of preoperative simulation.

In validating the segmentation algorithm, we found comparable results between AI-based segmentation using MRI and manual reconstruction by the dedicated radiological technicians using CT, but the accuracy of the depiction of the vesical arteries was relatively low in the CT-based reconstruction. The depiction of the CT-based 3D image depends on each dedicated radiological technician, leading to the possibility of underestimating narrow vessels that are difficult to interpret. In this regard, an AI-based algorithm can offer stable results independent of human capability, the efficiency of which should be validated in the future. Furthermore, given that the performance of AI-based segmentation can be improved by using the more abundant ground-truth label data with high quality, the future algorithm has a chance to be superior to CT-based reconstruction. We consider that there may be another

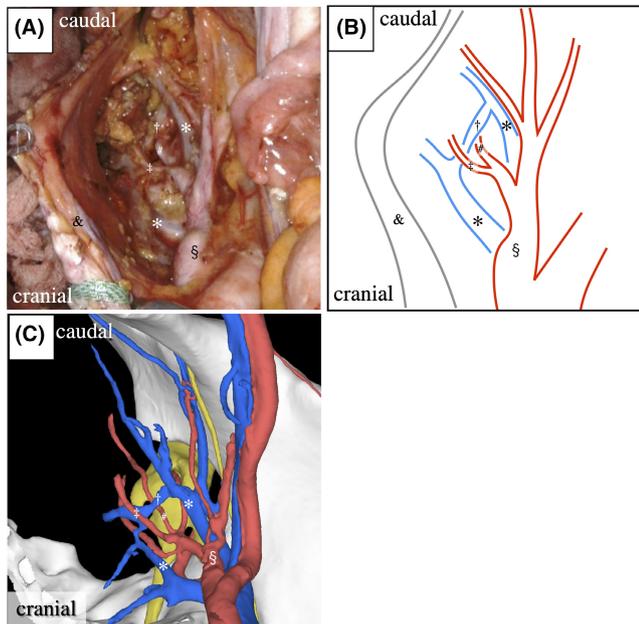


FIGURE 3 Representative case with a vascular anomaly. (A) Intraoperative image of the right lateral pelvic cavity. (B) Schema of the lateral pelvic cavity. (C) Three-dimensional image created by the artificial intelligence-based algorithm. Red, artery; blue, vein; yellow, nerve; white, bone. † Bridging vein between the two internal iliac veins; ‡ inferior vesical artery; § internal iliac artery; * internal iliac veins; # internal pudendal artery; & ureter.

possibility that combining the findings of both CT and MRI can improve the quality of the 3D model, and that various approaches should be taken into account to make the algorithm better.

Various organs are contained in the pelvic cavity other than the organs that are segmented with the current algorithm. Among these organs, the pelvic muscles would be the most significant targets of interest for colorectal surgeons, including the internal obturator muscle, piriformis muscle, levator ani muscle, and coccygeal muscle. MRI can provide a clear visualization of the muscular contour, and we consider that it would be sufficiently possible to make an algorithm for muscular segmentation. It is especially important in highly difficult surgery for advanced tumors that the interrelationship between vascular structure and muscles has to be comprehended prior to surgery (e.g. the relationship between the coccygeal muscle and internal obturator pudendal artery at Alcock's canal). We also consider that identifying the pelvic plexus would be crucial and tried to make ground-truth labels of the nerve. However, the plexus was so minute that it seemed to be a difficult task to achieve this aim; therefore, we initially started to find the sacral plexus or obturator nerve given that the previous technology could not have successfully identified nerve structures automatically. In the next step of this study, we aim to make a new algorithm that can perform segmentation of the pelvic muscles, as well as the pelvic plexus.

This study has several limitations. First, this system cannot be applied in patients for whom the quality of MRI is poor due to external factors, such as motion artifacts or the effect of an artificial

joint. Second, there seems to be room for improvement in the segmentation accuracy for vessels. This accuracy is going to be refined continuously. Furthermore, other anatomies related to rectal cancer surgery, such as hypogastric nerves or muscle, are not able to be segmented with the current algorithm. Third, this study was dedicated to the development of an algorithm targeting surgery for rectal cancer; therefore, we need to validate the potential of applying this system to other diseases.

In conclusion, we established an AI-based algorithm to automatically segment intrapelvic anatomies from 3D MRI that can be utilized for surgical simulation in the treatment of advanced rectal cancer. This system has potential to gain prominence considering its superior usability.

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Registry of the Study: N/A.

Animal Studies: N/A.

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