Magnetic resonance imaging–based synthetic computed tomography of the lumbar spine for surgical planning: a clinical proof-of-concept

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OBJECTIVE Computed tomography scanning of the lumbar spine incurs a radiation dose ranging from 3.5 mSv to 19.5 mSv as well as relevant costs and is commonly necessary for spinal neuronavigation. Mitigation of the need for treatment-planning CT scans in the presence of MRI facilitated by MRI-based synthetic CT (sCT) would revolutionize navigated lumbar spine surgery. The authors aim to demonstrate, as a proof of concept, the capability of deep learning–based generation of sCT scans from MRI of the lumbar spine in 3 cases and to evaluate the potential of sCT for surgical planning.

METHODS Synthetic CT reconstructions were made using a prototype version of the “BoneMRI” software. This deep learning–based image synthesis method relies on a convolutional neural network trained on paired MRI-CT data. A specific but generally available 4-minute 3D radiofrequency-spoiled T1-weighted multiple gradient echo MRI sequence was supplemented to a 1.5T lumbar spine MRI acquisition protocol.

RESULTS In the 3 presented cases, the prototype sCT method allowed voxel-wise radiodensity estimation from MRI, resulting in qualitatively adequate CT images of the lumbar spine based on visual inspection. Normal as well as pathological structures were reliably visualized. In the first case, in which a spiral CT scan was available as a control, a volume CT dose index (CTDI_{vol}) of 12.9 mGy could thus have been avoided. Pedicle screw trajectories and screw thickness were estimable based on sCT findings.

CONCLUSIONS The evaluated prototype BoneMRI method enables generation of sCT scans from MRI images with only minor changes in the acquisition protocol, with a potential to reduce workflow complexity, radiation exposure, and costs. The quality of the generated CT scans was adequate based on visual inspection and could potentially be used for surgical planning, intraoperative neuronavigation, or for diagnostic purposes in an adjunctive manner.

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KEYWORDS lumbar spine; image conversion; imaging; deep learning; machine learning; artificial intelligence

IN complex lumbar spinal conditions such as spondylolisthesis, kyphoscoliosis, or spinal tumors, the combination of MRI and CT have long proven complementary. Whereas CT imaging perfectly visualizes osseous structures and allows for assessment of spinal integrity and stability, MRI excels at delineating soft-tissue and nervous system structures with high contrast. CT images are often required for neuronavigation and treatment planning, such as for image-guided navigated biopsies or pedicle screw placement.¹

However, CT scanning is inherently coupled to radia-

tion exposure; an average lumbar spinal CT study equals an effective dose of around 3.5 mSv up to 19.5 mSv.^{2–6} In addition, multiple imaging sessions increase the patient burden and overall costs and introduce complex workflows, with the potential for intermodality registration errors. For these reasons, MRI-only workflows have gained attention in recent years.^{7,8}

In this brief report, we evaluate a prototype of the “BoneMRI” method, for the first time applied to the lumbar spine, that allows generation of synthetic CT (sCT) images from generally available MRI based on deep learn-

ABBREVIATIONS sCT = synthetic CT; T1W = T1-weighted; T2W = T2-weighted.

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FIG. 1. Case 1 (test data set). **A and D:** Conventional T2W MR images acquired on a 1.5T scanner. **B, E, C, and F:** Synthetic CT images generated from the BoneMRI sequence (B and E), along with the ground truth spiral CT scans (C and F). Midsagittal and axial (L5 pedicles) cuts are displayed in the upper and lower panels, respectively. This patient's BoneMRI sequence was acquired with a field of view width of 7.2 cm, with the transverse processes being cut off consequently.

ing. In this proof-of-concept study, we hypothesized that MRI-based sCT images can be used for surgical planning, potentially rendering planning CT scans superfluous.

Methods

Overview

We utilized a research prototype of the BoneMRI sCT generation method (BoneMRI, MRIGuidance B.V.), which is based on preliminary work.^{9–11} The deep learning model was trained using paired MRI and CT data, partly obtained in the context of this study and partly in other studies.^{9–11} We included 9 patients who were scheduled for robotic lumbar fusion surgery, of whom 8 were used in the training set, independent from the test set. The test set consisted of one of the 9 included patients scheduled for lumbar fusion surgery and 2 volunteers.

Image Acquisition

CT images were acquired in the supine position using a Philips ICT 256 scanner (318 slices, 1-mm thickness) and a lumbar spine protocol with iDose reconstruction. MR images were acquired in a fixed supine position using a Siemens Magnetom Essenza (1.5T field strength).

A standard lumbar spine protocol including conventional T1-weighted (T1W) and T2-weighted (T2W) sequences (acquisition time 15 minutes and 4 seconds), was complemented by a sagittal 3D radiofrequency-spoiled T1W multiple gradient echo) sequence for BoneMRI reconstruction (2 echoes; TR 7 msec, TE1 2.1 msec, TE2 4.2 msec; FOV 250 × 250 × 90 mm; reconstructed voxel size 0.74 × 0.74 × 0.9 mm, acquisition time 3 minutes and 53 seconds). This dedicated sequence utilized a high-frequency encode bandwidth (BW > 500 Hz/pix) to minimize potential geometrical distortions.

Model Development

Synthetic CT scans were generated from MRI inputs using a patch-based convolutional neural network, similar to U-Net, with CT scans as the ground truth.^{9,12} The model inputs consisted of 4D MRI scans with 3 spatial dimensions and 1 channel dimension.⁹ The network was implemented in Keras¹³ with a TensorFlow backend (Google Brain Team, Google LLC).

Proof-of-Concept Study

The prototype algorithm was applied to 3 subjects: 1

FIG. 2. Case 1 (test data set). Comparison of 3D volume renderings of the lumbar spine calculated from conventional CT (**A–C**) and from an sCT generated from the BoneMRI sequence in the same patient (**D–F**). Posterior (**A** and **D**), lateral (**B** and **E**), and oblique (**C** and **F**) views are provided. This patient's BoneMRI sequence was acquired with a field of view width of 7.2 cm, with the transverse processes being cut off consequently.

patient scheduled for lumbar fusion surgery (case 1) and 2 healthy volunteers (cases 2 and 3). In case 1, conventional T1W and T2W MRI sequences as well as the BoneMRI sequence and the generated sCT scans were available, along with a conventional CT scan of the lumbar spine. For cases 2 and 3, we tested the algorithm in its intended use case; only a BoneMRI sequence of the lumbar spine

was available, and from it an sCT scan was generated. These 3 individuals were never before encountered by the algorithm, thus representing a valid test object. Multiplanar reconstructions and 3D volume renderings were generated in RadiAnt Version 2020.1, and manual as well as semiautomated measurements and pedicle screw trajectory planning were carried out in Surgimap Version 2.3.2.1.

TABLE 1. Exemplary measurements performed comparatively on synthetic CT and spiral CT in case 1

Measurement	sCT	Spiral CT	Difference
L3			
Anterior VBH	26.5	26.5	0.0
Posterior VBH	32.0	31.8	0.2
Spinal canal diameter	14.9	15.0	-0.1
L4			
Anterior VBH	27.2	26.8	0.4
Posterior VBH	29.3	28.9	0.4
Spinal canal diameter	19.1	18.9	0.2
L5			
Anterior VBH	29.1	29.1	0.0
Posterior VBH	11.8	12.0	-0.2
Spinal canal diameter	24.8	25.6	-0.8
Total (MAD $\pm$ SD)	0.26 $\pm$ 0.24		

MAD = mean absolute difference; VBH = vertebral body height. Measurements are provided in millimeters.

Ethical Considerations

The development and proof-of-concept testing of the model and the associated use of patient data were approved by the local ethics review board (Medical Ethics Committees United). All patients signed informed consent forms that allow for the use of their data for research and publication purposes.

Results

Synthetic CT images of the lumbar spines of all 3 cases were successfully generated from BoneMRI sequences. Based on visual inspection, the quality of the sCT scans was adequate.

Figure 1 illustrates a comparison of T2W MRI, spiral CT, and sCT images in case 1. In this case, a spiral CT scan was available as a control with a volume CT dose index of 12.9 mGy that could thus have been avoided. Three-dimensional volume renderings of the lumbar spine were also calculated from both spiral CT and sCT scans for comparison (Fig. 2). In addition, exemplary comparative measurements of anterior and posterior vertebral body height and spinal central canal diameter were performed in case 1 (Table 1), with a mean absolute difference of 0.26 ± 0.24 mm.

To evaluate the proof-of-concept MRI-only surgical planning workflow, the algorithm was validated in 2 patients who did not undergo CT scanning (cases 2 and 3). Figure 3 illustrates the BoneMRI sequence and the sCT scans generated from it for both test cases. Normal as well as pathological structures were reliably visualized (e.g., the relevant spondylolisthesis of one of the volunteers). Figure 4 illustrates that conventional measurements such as spinal canal diameter, lumbar lordosis, and spondylolisthesis grading, as well as semiautomated measurements such as vertebral body segmentation could be carried out reliably on sCT. In addition, we were able to plan pedicle screw trajectories and screw thicknesses based on sCT.

Discussion

We show that generation of sCT images of the lumbar spine from MRI is feasible. The ability to visualize the osseous structures in 3D in a similar fashion as traditionally done using CT imaging without radiation and without the need for a separate second examination will be useful in the neurosurgical treatment of spinal disorders, both for diagnostic and therapeutic purposes such as in neuronavigation.

The use of image translation algorithms in medicine has previously gained interest in other applications—notably concomitant with an increase of combined use of MRI and CT in the field of radiotherapy.^{14,15} For example, generation of sCT scans from MRI has been described for radiotherapy purposes in the head and neck, pelvis, prostate, torso, and brain, again mostly for radiotherapy planning.^{16–21} A variety of atlas-based or voxel-based methods have been described, using different input sequences, as summarized by Florkow et al.⁹ Concomitantly, improvements in image processing techniques such as statistical or machine learning models have also helped the field leap forward.²¹ However, most applications have created substitute CT scans for radiation treatment planning purposes, often not achieving an image quality that would also be sufficient for diagnostic imaging or detailed neurosurgical planning. Apart from these aspects, generation of sCT scans of the lumbar spine has not previously been demonstrated, although preliminary work has been carried out focusing on the cervical spine.^{10,11}

The BoneMRI technique evaluated in this brief report is a deep learning–based method that requires dedicated input data obtained using a generally available sagittal 3D radiofrequency-spoiled T1W multiple gradient sequences, with its parameters carefully chosen in order to sensitize for specific tissue properties. Due to the dual-echo approach, information about proton density, water and fat fractions, relaxation constants, and susceptibility was intrinsically provided to the deep learning model.⁹ Indeed, the results of the BoneMRI technique appear promising in providing high-fidelity sCT images from MR images, with relevant improvements in elimination of radiation exposure, total examination time, and overall logistic efficacy.

An increase in MRI-only workflows has been seen in recent years.^{7,8} However, this would mean losing the radiodensitometric information provided by the CT scan, which is problematic because spine surgeons often require CT images to evaluate osseous anatomy such as dysplastic or twisted pedicles, and because MRI-based neuronavigation is still poorly implemented. In spinal neurosurgery, CT imaging has particular importance in surgical navigation, for example, for the computer-assisted insertion of pedicle screws.²² Thus, high-fidelity sCT imaging combined with navigation systems or surgical robotics^{22–25} could enable the concept of radiationless navigated surgery, enabling the use of computer assistance based on preoperative CT imaging without the need for additional radiation. Still, intraoperative fluoroscopy may be necessary for registration and instrumentation control, but these fluoroscopic doses are minor compared with those experienced by the patient during CT scanning.^{2,3,26,27} Of course, intraoperative CT imag-

FIG. 3. BoneMRI sequences acquired in 2 volunteers (cases 2 [upper] and 3 [lower]) not represented in the training data set (A and C), along with the corresponding sCT images generated (B and D). Midsagittal cuts of the lumbar spine are shown.

ing can also be particularly relevant in spine surgery, for acquisition of images for spinal neuronavigation based on the actual position of the patient on the operating table. Even under these circumstances, one could imagine the use of intraoperative MRI with generation of sCT scans instead of intraoperative CT, especially when considering the increased adoption of intraoperative MRI in neurosurgical departments,^{28,29} and the possibility for rapid MRI sequences.³⁰ In the near future, it is more likely that clinical applications of sCT scanning will focus around preoperative surgical planning for complex cases, implant sizing, and radiationless intraoperative navigation.

Limitations

The evaluated prototype algorithm is validated on limited data. Thus, although we show the results applied to 3 cases previously unseen by the algorithm, it has not yet been validated in patients with, for example, highly dysplastic or scoliotic pedicles, bone metastases, Modic-type endplate changes, and so forth. The limited amount of data prevents us from performing a thorough statistical analysis of geometric accuracy. However, we applied a high-frequency encode bandwidth to minimize potential geometrical distortion. In addition, previous work has demonstrated the robustness of sCT generation to specific degenerative spine diseases, also confirming geometric accuracy of sCT

in comparison with spiral CT.^{10,11} Furthermore, validation in patients with implants such as pedicle screws and rods, intervertebral cages, artificial intervertebral discs, neurostimulators, and interspinous process devices is required. Further development and validation on more patients are thus warranted, and the quality of the image might improve further with extended training. Similarly, to demonstrate the feasibility of using the generated sCT scans for accurate, near-radiationless robotic spine surgery, a case series is currently underway for clinical validation.

Conclusions

We show for the first time in the lumbar spine that, through the use of the BoneMRI acquisition sequence and convolutional neural networks, generation of sCT scans from MR images is feasible within minutes and with visually adequate sCT image fidelity. This novel method has the potential to reduce workflow complexity, radiation exposure, and costs associated with adjunctive CT scanning in the lumbar spine. The quality of the generated sCT scans—based on visual inspection—is sufficient for surgical planning and neuronavigation and may even suffice for diagnostics. Further validation of the method is warranted in patients with implants and other artifacts. Likewise, further development of the algorithm based on larger pa-

FIG. 4. Case 3. A midsagittal synthetic CT cut (**left**) in case 3 along with an axial reconstruction (**right**). Conventional measurements such as spinal canal diameter, lumbar lordosis, and spondylolisthesis grading (Meyerding grade II) as well as semiautomated measurements such as vertebral body segmentation were carried out. In addition, pedicle screw trajectories and screw thickness for both L5 pedicles were estimated on sCT imaging.

tient cohorts will likely improve image fidelity and consequently allow early clinical studies focusing on evaluating utility in surgical planning and intraoperative neuronavigation, as well as eventually radiationless robotic pedicle screw insertion.

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Disclosures

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Author Contributions

Conception and design: Staartjes, Seevinck, van Stralen, Schröder. Acquisition of data: Seevinck, van Stralen, Schröder. Analysis and interpretation of data: Staartjes, Seevinck, van Stralen, Schröder. Drafting the article: Staartjes. Critically revising the article: Seevinck, Vandertop, van Stralen, Schröder. Reviewed submitted version of manuscript: all authors. Approved the final version of the manuscript on behalf of all authors: Staartjes. Statistical analysis: Seevinck, van Stralen. Administrative/technical/material support: Seevinck, van Stralen, Schröder. Study supervision: Seevinck, Schröder.

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