Stability of conventional and machine learning-based tumor auto-segmentation techniques using undersampled dynamic radial bSSFP acquisitions on a 0.35 T hybrid MR-linac system

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(Received 4 August 2020; revised 8 December 2020; accepted for publication 8 December 2020; published 9 January 2021)

**Purpose:** Hybrid MRI-linear accelerator systems (MR-linacs) allow for the incorporation of MR images with high soft-tissue contrast into the radiation therapy procedure prior to, during, or post irradiation. This allows not only for the optimization of the treatment planning, but also for real-time monitoring of the tumor position using cine MRI, from which intrafractional motion can be compensated. Fast imaging and accurate tumor tracking are crucial for effective compensation. This study investigates the application of cine MRI with a radial acquisition scheme on a low-field MR-linac to accelerate the acquisition rate and evaluates the effect on tracking accuracy.

**Methods:** An MR sequence using tiny golden-angle radial k-space sampling was developed and applied to cine imaging on patients with liver tumors on a 0.35 T MR-linac.

Tumor tracking was assessed for accuracy and stability from the cine images with increasing k-space undersampling factors. Tracking was achieved using two different auto-segmentation algorithms: a deformable image registration B-spline similar to that implemented on the MR-linac and a convolutional neural network approach known as U-Net.

**Results:** Radial imaging allows for increased temporal resolution with reliable tumor tracking, although tracking robustness decreases as temporal resolution increases. Additional acquisition-based artifacts can be avoided by reducing the angle increment using tiny golden-angles. The U-net algorithm was found to have superior auto-segmentation metrics compared to B-spline. U-net was able to track two well-defined tumors, imaged with just 30 spokes per image (10.6 frames per second), with an average Dice coefficient $\geq 83\%$, Hausdorff distance $\leq 1.4$ pixel, and mean contour distance $\leq 0.5$ pixel.

**Conclusions:** Radial acquisitions are commonplace in dynamic imaging; however, in MR-guided radiotherapy, robust tumor tracking is also required. This study demonstrates the in vivo feasibility of tumor tracking from radially acquired images on a low-field MR-linac. Radial imaging allows for decreased image acquisition times while maintaining robust tracking. The U-net algorithm can track...
a tumor with higher accuracy in images with undersampling artifacts than a conventional deformable B-spline algorithm and is a promising tool for tracking in MR-guided radiation therapy. © 2020 The Authors. Medical Physics published by Wiley Periodicals LLC on behalf of American Association of Physicists in Medicine. [https://doi.org/10.1002/mp.14659]

**Key words:** auto-segmentation, golden-angle, machine learning, MR-linac, tumor tracking

### 1. INTRODUCTION

Effective tumor management using radiation therapy requires a maximal dose of radiation to the target volume. Ideally, this volume should only encompass the volume of the tumor including the microscopic tumor extension; however, inter- and intrafractional positioning errors and intrafractional organ motion require that additional error margins are applied. These margins increase the radiation dose to healthy tissue and ultimately limit the dose to the tumor.

Image-guided radiation therapy (IGRT),1–3 which incorporates imaging techniques into the radiation therapy workflow, allows for the direct determination of organ or tumor position. This information can result in a reduction in tumor error margins either through adapting treatment planning to inter- or intrafractional variations in patient anatomy,4 incorporation of motion into treatment planning,5 gated radiation delivery,6 or by multi-leaf collimator (MLC) adaptations based on tumor shape and position.7

The advantages of incorporating magnetic resonance imaging (MRI) into the radiation therapy workflow, known as MR-guided radiation therapy (MRgRT), are that MRI provides excellent soft tissue contrast with no additional ionizing radiation or invasive procedures. As hybrid MR-linac systems enter the clinical routine, it is possible to utilize dynamic MRI sequences to visualize motion in real-time, in which a series of images is rapidly acquired. MRgRT has been demonstrated to enable increased radiation dose to the target area through MLC updates7,8 as well as through gating and has shown promising results in patient studies for the reduction of error margins.9,10

An increasing number of research studies have focused on the development of tumor tracking techniques from dynamic MR imaging. These approaches include auto-contouring, in which the tumor contour is generated through algorithms such as neural networks,11 particle filtering,12 and feature tracking algorithms, in which certain key points in the image are detected and followed over time.13,14 Finally Template matching, in which an image of the tumor (the template) is searched for in the subsequent images in the dynamic MR series.15–18

In terms of MR sequence development, dynamic MRI using a radial k-space trajectory is known to have numerous benefits. In particular, the oversampling of the k-space center leads to robustness against motion artifacts due to the inherent k-space averaging at low spatial frequencies.19 Azimuthal undersampling of k-space results in streaking artifacts in the image domain rather than the ghosting that occurs from Cartesian undersampling, which are more benign in terms of image quality and allow for higher acceleration factors in comparison to Cartesian acquisitions, as can be demonstrated in MR angiography.20 To this end, dynamic radial imaging has been successfully applied in joint kinematics,21 cardiac cine imaging,22 and speech imaging.23 Furthermore, radial MR imaging can be effectively combined with a “sliding window” reconstruction technique,21,24 in which spokes are shared between multiple time frames. This is particularly effective when the golden ratio is used as an angular increment between spokes.25

In this study, a dynamic balanced steady-state free-precession (bSSFP) radial MR imaging sequence is developed for tumor tracking on a 0.35 T MR-linac system. In addition, the limits of tracking accuracy are investigated with respect to the imaging frame rate by azimuthal k-space undersampling and non-Cartesian SENSE reconstruction.26,27

To assess tracking fidelity in the presence of k-space undersampling, two tracking algorithms were implemented: first, a B-spline interpolated deformable registration algorithm, which has been previously used to segment abdominal cancer,24 was chosen because the software of the low-field system used in this study implements a similar algorithm for intrafractional tumor tracking.28 Second, the U-net algorithm,29 which is a convolutional neural network approach that requires relatively little data for learning and has also been shown to be highly successful for medical image segmentation.30 Data are acquired from a motion phantom and in vivo cases from patients undergoing treatment for liver cancer.

### 2. MATERIALS AND METHODS

#### 2.A. MR-linac system

All imaging was performed on an MRIdian Linac system (ViewRay Inc., Cleveland, Ohio, USA), with a magnetic field strength $B_0$ of 0.35 T, using two corresponding clinical 6-channel surface receiver coils for the torso. Reconstruction and postprocessing were performed on a 64-bit Windows 10 PC with Intel Core i7-6700 CPU and 32 GB RAM.

#### 2.B. MR sequence

A balanced steady-state free-precession (bSSFP) sequence was implemented in order to maximize the received MR signal31 by balancing all gradients within TR. Data were acquired along a radial readout trajectory using golden-angle increments. Two golden-angles were compared, namely the true golden-angle $\psi = 111.25^\circ$32 and the 10th tiny golden-angle $\psi_{10} = 16.95^\circ$.33
All images were acquired in the sagittal orientation and had the following parameters unless otherwise stated: voxel size \((\Delta x)^3 = 2.3 \times 2.3 \times 7.5 \text{ mm}^3\); field of view = \(300 \times 300 \text{ mm}^2\); TR/TE = 3.14 ms/1.57 ms, flip angle = 90°.

### 2.C. Image reconstruction

Radial images were reconstructed using an iterative SENSE reconstruction\(^{26}\) algorithm implemented with SigPy\(^{34}\) in Python3 (Python Software Foundation, Wilmington, Delaware, USA). The reconstruction method solves the following equation:

\[
\min_x \frac{1}{2} \| GFSx - y \|_2^2 + \frac{\lambda}{2} \| x \|_2^2,
\]

where \(G\) is the gridding operator, \(F\) is the Fourier operator, \(S\) is the SENSE operator, \(x\) is the reconstructed image, and \(y\) is the acquired k-space data. The required coil sensitivity maps were estimated by ESPIRIT\(^{35}\) based on fully sampled images. Based on empirical data, the regularization parameter was set to 7.0. Undersampled Cartesian imaging were reconstructed using GRAPPA reconstruction\(^{36}\) implemented with pygrappa.\(^{37}\)

The temporal resolution of the dynamic series was retrospectively determined by the implementation of a sliding window reconstruction scheme. The length of the reconstruction window varied from 10 to 128 spokes per frame, allowing for the same data to be reconstructed multiple times at different temporal resolutions. For comparison of the images at different temporal resolutions, the center spokes of the individual frames were kept constant, as shown in Fig. 1.

### 2.D. Data processing

A sequence of 50 images reconstructed from 128 spokes, representing a duration of 20 s, was used to investigate the tracking performance. The ground truth for the tumor shape and location in each frame was taken to be the manual segmentation of the tumor. The same tumor contours were used for the sequences with reduced reconstruction windows, as all undersampled frames were centered at identical times with the fully sampled frames. Within the sequence used for defining the ground truth, 50 additional contours were drawn in the same images by the same observer as well as a second observer for an intra- and interobserver comparison to evaluate the reproducibility of manual contouring.

### 2.E. Motion phantom

An in-house built motion phantom\(^{38}\) was used to execute precise movements, driven by a commercial CIRS motor (CIRS Inc., Norfolk, Virginia, USA). A movable cylinder was filled with a mixture of 2.2% agarose and 0.4 mM gadopentate dimeglumine gadolinium contrast agent to simulate liver tissue,\(^{39}\) whose relaxation times\(^{39}\) \((T_1 = 560 \pm 7 \text{ ms}, T_2 = 47.5 \pm 0.9 \text{ ms})\) measured at 1.5 T are in accordance with the literature.\(^{40}\) Within the cylinder, the motion of a single hollow plastic aere with contrast gel was tracked [Fig. 2(a)]. The motor was programmed to run with a \(\sin^4\) trajectory with 4 cm peak-to-peak amplitude and 6 s breathing cycle to simulate free breathing motion. The reconstruction window was set to 128 spokes. This phantom was also used to compare the true and tiny golden-angle.

### 2.F. Patient study

Three liver tumors from two patients of 57 and 76 yr undergoing radiation therapy were imaged during free breathing (Fig. 3); each tumor exhibited a different size, motion range, and image contrast. The patients were imaged using a bSSFP sequence with a radial sampling scheme using the 10th tiny golden-angle increment and a Cartesian sampling scheme. The study was conducted in accordance with the Declaration of Helsinki. Institutional review board approval was obtained, and all subjects provided written informed consent.

To validate the tracking methods also on clinical cine images, tracking was performed in an additional liver patient imaged with the vendor-supplied bSSFP sequence acquired with 4 fps, which uses Cartesian sampling [Fig. 2(b)].

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**Fig. 1.** Image reconstruction of the radial acquisitions. (a): Retrospective undersampling was performed by reducing the reconstruction window while keeping its center position fixed to allow comparison between undersampled images at the same point in time. (b): Example images showing the different time resolutions including number of spokes (sp) as well as the corresponding frames per second (fps).
2.G. Tracking methods

Two different tracking methods were compared in this study: U-net, a convolutional neural network, and B-spline, a deformable image registration. Both methods use a 128 × 128 pixel input image and output a binary mask of the tumor contour.

2.G.1. U-net

The U-net architecture\(^{29}\) was implemented with Keras in Python. The Adams optimizer was used with binary cross-entropy loss as a metric. The following network hyperparameters were used: \(\text{epochs} = 150\), \(\text{batch size} = 1\), and initial learning rate \(10^{-5}\), which was reduced by a factor of 10 when the loss function did not improve during the preceding 3 epochs.

In contrast to the original paper, a dropout of 0.5 was added after each max-pooling operation at the encoder part.
and after each concatenation at the decoder part to prevent overfitting. Moreover, batch normalization was added to each convolution layer.

Image augmentation was performed to increase the variability of training with the following parameters: height shift = 10%, width shift = 5%, rotation range = 5°, shear range = 10°.

2.1. Evaluation metrics

The results of the auto-contouring are quantified with one area-based and two contour-based metrics.

The Dice coefficient \(\text{dice}(A,B) = \frac{2|A \cap B|}{|A| + |B|}\) measures the normalized spatial overlap of two areas and takes values between 0% for no overlap and 100% if both areas are the same.

The Hausdorff distance represents the longest connection between one point of one set to the closest point of the other set and is defined as \(\text{HD}(A,B) = \max(hd(A,B),hd(B,A))\), where \(hd(A,B) = \max_{a \in A} \left( \min_{b \in B} (\|a - b\|) \right)\).

The mean contour distance calculates the mean distance between two contours and is defined as \(\text{MCD}(A,B) = \max(mcd(A,B),mcd(B,A))\), where \(mcd(A,B) = \min_{a \in A} \left( \min_{b \in B} (\|a - b\|) \right)\).

2.2. B-spline

The B-spline tracking was implemented as a multistep process. First, for each frame of the cine sequence, the most similar frame out of 10 reference images was evaluated by cross correlation. Second, the B-spline algorithm calculates a nonrigid deformation map between these two images. Finally, this map is applied to the manual contour of the reference image to achieve the contour of the current frame.

2.3. Testing framework

Prior to auto-segmentation of the tumors in the cine frames, 10 manually segmented images were used so that U-net could learn the kernel weights, as well as for the B-spline registration to determine the reference image. The remaining 40 images were used for testing.

A fivefold cross validation was performed to increase the statistical significance for both tracking methods. The cross validation did not use shuffling to ensure that each set of 10 adjacent training images automatically represent all breathing states. For each of the five iterations, the images were split into a training set of 10 images and a test set of 40 images. Therefore, each frame was used for training once and 200 frames were evaluated in total.

3. RESULTS

Figure 4 shows the difference in image quality between the 1st and 10th golden and tiny golden-angle increments. As more discernible artifacts can be observed in the image acquired at the true golden-angle, all further experiments were conducted using tiny golden-angle.

The selection method of the reconstruction window is shown previously in Fig. 1(a) and reconstructs the image frames to depict the same point in time, independent of the number of spokes used in the reconstruction. An example of the resulting image reconstruction for various temporal resolutions can be seen in Fig. 1(b). The reduction of the number of spokes in the reconstruction results in an increasing prominence of streaking artifacts in the images; however, even for images with high undersampling factors, large spatial structures in the images, such as the liver, are still observable. This is in contrast to undersampled Cartesian images (Fig. 5), for which it becomes challenging to depict large structures in the image.

The inter- and intraobserver comparison of tumor segmentation, summarized in Table I, shows that Tumor 1 has the highest Dice conformity within and between both observers. Tumors 1 and 2 have well-defined contours, which is reflected in similarly low Hausdorff and mean contour distances, in contrast to Tumor 3. Despite the similarity of these two metrics, the Dice coefficient of Tumor 2 is low as it contains relatively few pixels, which quickly leads to large variations in the Dice coefficient even for small variations in the segmentation. Tumor 3 has a contour that was less definable in certain frames, resulting in the worst results of the intra- and interobserver comparison.

The tracking results of the motion phantom, shown in Table II, demonstrate that the U-net contouring method is in good agreement with the ground-truth user segmentation, being within 1 standard deviation of the intraobserver variation for all metrics. B-spline performs less effectively in this case.

The mean values of the tracking of the liver patient imaged with the Cartesian product sequence are within 1 standard deviation of the intraobserver comparison for the U-net and within 2 standard deviations for B-spline for all metrics (Table II).

Examples of auto-contouring on the radially acquired images for the three liver tumors are shown in Fig. 3. The

\[
\psi_{10} = 111.25° \quad \psi_{10} = 16.95°
\]

Fig. 4. Reduction of image artifacts (arrows) by reducing the angle increment between spokes from the true golden-angle \(\psi_1 = 111.25°\) (a) to the \(10^{th}\) tiny golden-angle \(\psi_{10} = 16.95°\) (b).
tumors were located in different regions of the liver and varied in size from 18 to 130 pixels. Differences in contrast between the tumor and healthy liver were also observed across all three cases. Tumor motion was determined to be highly subject specific, with Tumor 3 exhibiting the largest motion in the head–foot and anterior–posterior directions, and Tumor 2 exhibiting the smallest. The motion is most likely due to a combination of tumor position and subject breathing style. The breathing pattern shows that approximately 10 sequential frames include all breathing phases.

The box plots in Fig. 6 summarize the performance of U-net and B-spline tracking with increasing azimuthal undersampling factor. In general, tracking robustness decreases as the undersampling factor increases, as can be determined by an increasing interquartile range and increased number of outliers. This is most likely due to more prevalent image artifacts, which confound the auto-contouring algorithms. It can be seen that in most cases, U-net outperforms the B-spline method. Although the robustness of the tumor tracking is subject dependent, it was determined from the data that the median value for all performance metrics except for the Hausdorff distance of Tumor 1 was within 2 standard deviations of the intraobserver measurement down to images with 30 spokes/frame using U-net and 80 frames/image using B-spline.

For U-net tracking with images with more than 20 spokes, the mean contour distance of Tumors 1 and 2 is on average ≤ 0.5 pixel and the Dice coefficient of Tumor 1 is ≥ 90%.

Both tracking methods show comparable performance between radial and Cartesian images (Fig. 7), where Cartesian images have 128 fully sampled lines and radial images have 128 spokes. U-net outperforms B-spline in all radial and Cartesian image series of the three tumors.

In terms of computation time, calculation duration was 53 ms/frame for U-net and 7000 ms/frame for B-spline. In addition, U-net required 7.5 min of learning. The most time-consuming stage of B-spline was finding the most similar reference image, while the second stage took only 1300 ms for contouring per frame.

4. DISCUSSION

Certain components of the MR-linac system used in this study are unconventional in comparison to common

![Figure 5](image_url) Comparison of undersampling effects in radial and Cartesian images acquired in 128 repetition times (TR) and 32 TR, corresponding to 2.5 and 10.0 fps, respectively. The tumor (arrow) is clearly visible in the fully sampled Cartesian image with 128 lines, but not visible in the Cartesian image with 32 lines using GRAPPA (Grappa factor = 5, number of center lines = 7) due to noise. The radial image with 128 spokes already exhibits minor streaking artifacts due to small undersampling. Nevertheless, the tumor is visible in both radial images, as streaking artifacts are less disruptive than noise. Differences in the contrast between radial and Cartesian images are due to the density compensation in the radial reconstruction.

| Table I. Intra- (1 vs 1) and interobserver (1 vs 2) comparison of the three liver tumors with radial acquisition. Analyzed were the 50 cine frames with a reconstruction window of 128 spokes, which were used to draw manual contours. |

| Metric                  | Tumor 1 | Tumor 2 | Tumor 3 |
|-------------------------|---------|---------|---------|
|                         | 1 vs 1  | 1 vs 2  | 1 vs 1  | 1 vs 2  | 1 vs 1  | 1 vs 2  |
| Dice coefficient in %   | 94 ± 3  | 83 ± 5  | 89 ± 7  | 76 ± 11 | 88 ± 5  | 76 ± 9  |
| Hausdorff distance in pixels | 1.0 ± 0.1 | 1.9 ± 0.5 | 1.0 ± 0.2 | 1.2 ± 0.4 | 2.3 ± 0.9 | 8.6 ± 5.6 |
| Mean contour distance in pixels | 0.3 ± 0.1 | 0.7 ± 0.2 | 0.3 ± 0.2 | 0.6 ± 0.2 | 0.7 ± 0.3 | 2.4 ± 1.5 |

| Table II. Tracking results of the contrast sphere in the motion phantom [Fig. 2(a)] and the liver tumor of the clinical cine [Fig. 2(b)]. |

| Metric                  | Motion phantom | Clinical cine |
|-------------------------|----------------|--------------|
|                         | Intraobserver comparison | Tracking | Intraobserver comparison | Tracking |
| Dice coefficient in %   | 96 ± 2 | U-net: 96 ± 3 | U-net: 87 ± 5 |
|                         |       | B-spline: 88 ± 18 | B-spline: 82 ± 8 |
| Hausdorff distance in pixels | 1.3 ± 0.4 | U-net: 1.2 ± 0.4 | U-net: 1.3 ± 0.4 |
|                         |       | B-spline: 2.0 ± 2.8 | B-spline: 1.7 ± 0.7 |
| Mean contour distance in pixels | 0.4 ± 0.2 | U-net: 0.4 ± 0.2 | U-net: 0.5 ± 0.2 |
|                         |       | B-spline: 1.0 ± 1.5 | B-spline: 0.6 ± 0.3 |
diagnostic MR scanners, and as such, imaging parameters were re-optimized for this system. In particular, reducing the azimuthal increment between spokes from true golden-angle to tiny golden-angle substantially reduced artifacts during radial imaging, as can be seen in the motion phantom images (Fig. 4). The artifact reduction is most likely due to a reduction of the eddy current effects by slower switching of the gradients,\textsuperscript{33} although a full characterization of the gradient hardware on the MR-linac was not performed as part of this study.

The inter- and intraobserver variability in tumor segmentation was found to be subject specific, with tumor shape, definition, contrast, and size presumably having influence. The ground truth to which the performance of the auto-contouring methods was compared was defined by the segmentation of a single observer, which is therefore also subject to internal variation.

In initial validations, the performance of the U-net and B-spline auto-contouring methods was assessed in Cartesian clinical images and radially acquired images of a motion...
phantom. It can be seen that U-net has a performance advantage over B-spline. Phantom experiments can demonstrate proof-of-concept, but the phantom used in this study is not an adequate representation of a real tumor.

Figure 5 shows a visual comparison between radial and Cartesian images for two different temporal resolutions. For lower temporal resolutions, image quality is comparable. At higher temporal resolution, large features in the radial images, such as the liver tumor, remain clearly identifiable despite streaking artifacts, which are typical for undersampled radial imaging. In the Cartesian images, noise amplification associated with the acceleration factor of the GRAPPA reconstruction makes the tumor and liver difficult to visualize. A full comparison of radial and Cartesian imaging is challenging to perform due to the different reconstruction techniques involved. In this study, it was decided to focus on the performance of radial imaging for tumor tracking and the extent to which k-space can be undersampled while maintaining robust tracking.

In the radial in vivo investigations, tracking stability for different undersampling factors was assessed. It can be seen from Fig. 6 that U-net outperformed B-spline in almost every test setting, independent of the tumor or temporal resolution. In some cases at very high temporal resolution, U-net was unable to detect the tumor. The B-spline method was able to detect the tumor in every image independent of the temporal resolution.

In general, auto-contouring becomes more uncertain with increasing temporal resolution for both tracking methods due to a decreased amount of reconstructed data leading to more prominent undersampling artifacts. An increasing uncertainty in the tumor contours will lead to increased error margins during therapy, leading to a subject-dependent trade-off between temporal resolution and accuracy. In particular, using a golden-angle sampling strategy makes radial imaging highly flexible in this regard, with the potential of even real-time adjustments to the temporal resolution.

This trade-off between temporal resolution and accuracy may also be alleviated by an increase in the static B0 field of the MR scanner, as can be found in the systems of other MR-linac vendors. There is a theoretical increase in SNR increases with increasing B0; however, various factors contribute to SNR gain, such as receiver coil architecture and body part imaged. From the data in Fig. 6, it can be extrapolated that an increase in SNR will improve tracking stability; however, contrast changes in the tumor due to the B0 dependency of T1 and a higher sensitivity to banding artifacts in the bSSFP sequence will also play a role, leading to dependencies on the type and location of the tumor.

In a clinical workflow, failures in tracking, in which the tumor is incorrectly detected, must somehow be detected and the radiation must be stopped. This becomes more urgent at higher temporal resolution, where a small but increasing number of outliers in the tumor tracking were detected. Trivial detection metrics, such as large changes in tumor volume or nonphysiological changes in tumor location could be considered, at which point treatment could be temporarily suspended.

The tracking comparison of radial and Cartesian images of the three liver tumors shows similar accuracy (Fig. 7). To make this comparison as fair as possible, the Cartesian images were fully sampled and the radial images have been selected to have the same acquisition time.

Although the tracking implementations in this study were not optimized for performance, it can be noted that neural networks need multiple images for training, each with a manually defined segmentation and a prolonged learning phase, whereas the B-spline image registration requires in general only one reference image, but can be improved with multiple
images. U-net training requires only a few annotated images, such as 10 images used in this study, and is relatively fast compared to other neural network based approaches, allowing manual contouring in a few minutes.

Training duration can be further decreased with increased computational power or pretrained networks. When performed between the simulation session and treatment day, training duration is not crucial. Once the network is trained, it is fast at detecting tumors, with each frame requiring on the order of 10 ms using standard PC hardware. Although auto-contouring was performed offline in this study, real-time tracking is feasible for both methods with optimized, parallelized code and dedicated hardware including graphical processing units (GPUs).

5. CONCLUSION

This study demonstrates the feasibility of a radial acquisition scheme for tumor tracking at a 0.35 T MR-linac. To our knowledge, this is the first study of tumor tracking with radial imaging on a low-field MR-linac. Previous studies with MR-linacs either used Cartesian imaging at 0.35 T or radial imaging at higher field strength such as 1.5 T. Moreover, the study shows the potential to accelerate the temporal resolution of the image acquisition. The clinical routine uses Cartesian images with 4 fps. Radial imaging allows for higher undersampling factors, and this study shows that even with frame rates above 10 fps there is only little impact on the tracking performance for a well-defined tumor.

Two tracking methods were compared. In a previous comparative study, a deformable image registration performed better than a neural network. In this study, we found that the U-net neural network performs better than the deformable B-spline for both radial and Cartesian images.

Good image quality is crucial for any tracking method. Quality could be further improved with more advanced iterative image reconstruction algorithms or new methods like neural networks for image reconstruction to reduce under-sampling artifacts.

ACKNOWLEDGMENTS

The authors thank Dr. Philipp Mann for his support in setting up the motion phantom at the MR-linac and thank Markus Wunderlich for patient guidance. The installation of the MRI-dian Linac in Heidelberg was kindly funded by the German Research Foundation DFG (project number 281540677). Open Access funding enabled and organized by ProjektDEAL.

CONFLICT OF INTEREST

Juliane Hörner-Rieber and Sebastian Klüter have received speaker fees and travel reimbursement from ViewRay Inc. (Oakwood, USA).

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