Published in final edited form as:

Phys Med Biol. 2016 December 07; 61(23): 8276–8297. doi:10.1088/0031-9155/61/23/8276.

Performance Evaluation of MIND Demons Deformable Registration of MR and CT Images in Spinal Interventions

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Abstract

Accurate intraoperative localization of target anatomy and adjacent nervous and vascular tissue is essential to safe, effective surgery, and multimodality deformable registration can be used to identify such anatomy by fusing preoperative CT or MR images with intraoperative images. A deformable image registration method has been developed to estimate viscoelastic diffeomorphisms between preoperative MR and intraoperative CT using modality-independent neighborhood descriptors (MIND) and a Huber metric for robust registration. The method, called MIND Demons, optimizes a constrained symmetric energy functional incorporating priors on smoothness, geodesics, and invertibility by alternating between Gauss-Newton optimization and Tikhonov regularization in a multiresolution scheme. Registration performance was evaluated for the MIND Demons method with a symmetric energy formulation in comparison to an asymmetric form, and sensitivity to anisotropic MR voxel-size was analyzed in phantom experiments emulating image-guided spine-surgery in comparison to a free-form deformation (FFD) method using local mutual information (LMI). Performance was validated in a clinical study involving 15 patients undergoing intervention of the cervical, thoracic, and lumbar spine. The target registration error (TRE) for the symmetric MIND Demons formulation [1.3 ± 0.8 mm (median $\pm$ interquartile)] outperformed the asymmetric form [3.6 ± 4.4 mm]. The method demonstrated fairly minor sensitivity to anisotropic MR voxel size, with median TRE ranging 1.3 – 2.9 mm for MR slice thickness ranging 0.9 – 9.9 mm, compared to TRE = 3.2 – 4.1 mm for LMI FFD over the same range. Evaluation in clinical data demonstrated sub-voxel TRE (< 2 mm) in all fifteen cases with realistic deformations that preserved topology with sub-voxel invertibility (0.001 mm) and positive-determinant spatial Jacobians. The approach therefore appears robust against realistic anisotropic resolution characteristics in MR and yields registration accuracy suitable to application in image-guided spine-surgery.

Keywords

deformable image registration; Demons algorithm; symmetric diffeomorphism; multimodality image registration; MIND; CT; MRI; image-guided surgery

1. INTRODUCTION

Spine surgery is an increasingly common treatment for a wide range of spinal disorders (Smith and Fessler 2012), including spinal metastases (Haji *et al* 2011), trauma (Pieretti-Vanmarcke *et al* 2009, Fehlings and Wilson 2010, Patel *et al* 2010), and deformity (Sean Dangelmajer *et al* 2014, Juan S. Uribe *et al* 2014), with the past 20 years witnessing exponential increase in the number of spinal procedures performed in the United States (Bekelis *et al* 2014). A variety of factors can challenge safe delivery of spinal intervention and contribute to medical errors or complication such as wrong-level surgery (Mody *et al* 2008, Longo *et al* 2012, Groff *et al* 2013), vascular injury (Ziev B. Moses *et al* 2013), breach of spinal dura (Hashidate *et al* 2008, Strömquist *et al* 2012, Guerin *et al* 2012) or suboptimal device placement requiring revision surgery (Oliver P. Gautschi *et al* 2011, Ughwanogho *et al* 2012). Image-guided spine surgery (IGSS) helps to avoid such adverse events by improved visualization and navigation relative to target anatomy (e.g., vertebral levels and spinal malignancies) and critical structures (e.g., nerves and vessels) and has demonstrated improved surgical outcome in pedicle screw placement (Larson *et al* 2012b, 2012a, Flynn and Sakai 2013), deformity correction (Larson *et al* 2012b, Flynn and Sakai 2013), spinal fusion (Adogwa *et al* 2011, Tsahsarlis *et al* 2013, Tian *et al* 2013), trauma surgery (Schouten *et al* 2012), and resection of tumors (Bandiera *et al* 2013).

Surgical planning and identification of target anatomy are typically performed using preoperative images, including computed tomography (CT) or magnetic resonance (MR) imaging. The latter is often the preferred preoperative imaging modality for scenarios that require clear delineation of soft-tissue (e.g., the spinal cord, cerebrospinal fluid, nerve bundles, and vasculature). On the other hand, intraoperative imaging often involves CT or cone-beam CT (CBCT), owing to its speed, convenience, cost, and compatibility with the operating environment. Multimodality deformable image registration is therefore valuable in bringing preoperative MR images and the surgical plan into alignment with intraoperative CT or CBCT for intraoperative localization. Since the deformation of a particular patient's anatomy between preoperative and intraoperative imaging necessarily maintains topology and coherence of local motion with respect to changes in spinal curvature, multimodality deformable registration that estimates diffeomorphisms (Beg *et al* 2005, Avants *et al* 2008, Vercauteren *et al* 2009, Avants *et al* 2011, Reaungamornrat *et al* 2016a) is of particular interest.

Volumetric deformable image registration permits automatic estimation of non-rigid alignment between two images through maximization of image similarity. Mutual information (MI) and its normalized variants, for example, maximize statistical dependence of image intensities and are commonly applied for multimodality imaging (Pluim *et al* 2003). However, since such measures rely on an estimated joint intensity distribution, they

are sensitive to intensity non-uniformities (e.g., scatter artifacts in CT or shading artifacts in MR) and assume tissue (intensity)-class correspondence, which is a poor assumption for CT and MR (Xiahai *et al* 2011). Application of MI variants to deformable MR-CT registration is therefore challenging. Alternatively, images can be transformed into a consistent representation using modality-insensitive scalar-value or vector-value image transformations. An example scalar-value transformation is a distance map transform, as in (Reaungamornrat *et al* 2013). Vector-value transformations more uniquely represent rich structural/contextual information. For example, nonlocal-mean (NLM) based features have been proposed to capture local structures (Heinrich *et al* 2012) and local contexts (Heinrich *et al* 2013) in images from distinct imaging modalities. The modality-independent neighborhood descriptor (Heinrich *et al* 2012) – referred to herein as a “modality-insensitive” neighborhood descriptor (MIND) – for example, has been used to estimate an elastic deformation between MR and CT images of the lung.

Previous work (Reaungamornrat *et al* 2016a) presented a modality-insensitive deformable registration method, called MIND Demons, to estimate a diffeomorphism between MR and CT images of the spine using MIND descriptors and a robust Huber metric in a Demons-like optimization framework. This paper presents a performance evaluation of the MIND Demons method, examining three aspects that are important to clinical translation of the method. First, the performance of the (symmetric) MIND Demons implementation is compared to a variant with an asymmetric energy formulation (Reaungamornrat *et al* 2016b). Second, we investigated the sensitivity of the MIND Demons method to anisotropic voxel size, which is particularly common for preoperative MR images. Finally, we present an evaluation of the method in a clinical study with patient image data presenting broad variations in the degree of deformation, imaging protocols, image quality, and anatomical site (15 cases spanning the cervical, thoracic, and lumbar spine).

2. MIND DEMONS REGISTRATION

As shown in figure 1 and summarized below, the MIND Demons method estimates a pair of time-dependent diffeomorphisms $\phi_i: \Omega \subset \mathbb{R}^n \times t \in [0, 1] \rightarrow \Omega$ for $i \in \{0, 1\}$ ($n = 2$ or 3 for 2D or 3D, respectively) that yields a composed diffeomorphism $\psi(z, 0) = \phi_0(\phi_1^{-1}(z, 1), 0)$ mapping the domain of a moving image I_0 defined at time 0 to the domain of a fixed image I_1 defined at time 1 (i.e., maximizing similarity between MIND descriptors of $I_0 \circ \psi$ and that of I_1 , $m_{I_0 \circ \psi} \approx m_{I_1}$) in a multiresolution scheme using Demons alternating optimization. A complete derivation of the method with an analysis of parameter settings is in (Reaungamornrat *et al* 2016a). Since $\phi_i(x, t)$ are defined with respect to a Lagrangian frame in the domain of a virtual image $I_{0.5}$ at time 0.5, a morphological pyramid is constructed only for $I_{0.5}$ such that the finest resolution of $I_{0.5}$ is equal to that of I_1 . In each optimization iteration, $\phi_0(x, t)$ and $\phi_1(x, t)$ push the Lagrangian frame from the domain of $I_{0.5}$ to the domain of I_0 (at time 0) and to that of I_1 (at time 1), respectively, and MIND descriptors are recalculated. The computation of the descriptors uses continuous representations of I_0 and I_1 modelled through cubic B-spline interpolation. The method was implemented using the Insight Segmentation and Registration Toolkit (ITK) (Ibanez *et al* 2002) with nominal

parameter settings and convergence criteria as in (Reaungamornrat *et al* 2016a). The main components of the algorithm are summarized in the following subsections.

2.1. Modality-Insensitive Neighborhood Descriptor (MIND)

The MIND descriptor captures local structure information in a manner that is relatively insensitive to image intensities and thereby applicable to multi-modality image registration – e.g., registration of MR (I_0) and CT (I_1). Its computation uses a non-local mean operator (Buades *et al* 2005, Shechtman and Irani 2007) and involves points in a neighborhood indicated by a stencil $\mathcal{N}_S$. The 3D stencil used in this work is illustrated in figure 2. An element j of a MIND descriptor $\mathbf{m}_I(\mathbf{x})$ at a point $\mathbf{x}$ in an image I corresponds to a point $\mathbf{r}_j \in \mathcal{N}_S$ and is computed as:

$$m_{I,j}(\mathbf{x}) = c \exp\left(-\frac{d(I, \mathbf{x}, \mathbf{r}_j)}{V(I, \mathbf{x})}\right) \quad (1)$$

where c is a normalization factor making $\max_{j=1,2,\dots,|\mathcal{N}_S|} \{m_{I,j}(\mathbf{x})\} = 1$, and the similarity between a patch of $\mathbf{x}$ and that of $\mathbf{r}_j$ is measured using a sum of Gaussian-weighted square difference:

$$d(I, \mathbf{x}, \mathbf{r}_i) = \sum_{\mathbf{z} \in \mathcal{N}_p} G_{\sigma_p}(\mathbf{z}) (I(\mathbf{x} + \mathbf{z}) - I(\mathbf{r}_i + \mathbf{z}))^2 \quad (2)$$

where $\mathcal{N}_p$ is a neighborhood configuration of a patch, $\mathbf{z}$ is the offset from the center of $\mathcal{N}_p$, and G_{σ_p} is a Gaussian kernel with width σ_p . The local variance $V(I, \mathbf{x})$ at $\mathbf{x}$ in equation (1) is approximated by an average of patch distances between the patch of $\mathbf{x}$ and patches of its nearest neighboring points in $\mathcal{N}_S$.

2.2. Huber Distance as a Similarity Measure

The Huber distance metric combines the robustness against noise and outliers of the L^1 norm and the differentiability of the L^2 norm (Huber 1973). It is therefore a prevalent metric for robust numerical optimization (Werlberger *et al* 2009, Wang *et al* 2014). We compute the differences between the descriptors of I_0 , $\mathbf{m}_{I_0}$, and that of I_1 , $\mathbf{m}_{I_1}$, using the Huber distance:

$$S(\mathbf{m}_{I_0}, \mathbf{m}_{I_1}, \mathbf{x}) = \sum_{j=1}^{|\mathcal{N}_S|} \begin{cases} \frac{1}{2\varepsilon} (m_{I_0,j}(\mathbf{x}) - m_{I_1,j}(\mathbf{x}))^2, & \text{if } 0 \leq |m_{I_0,j}(\mathbf{x}) - m_{I_1,j}(\mathbf{x})| \leq \varepsilon \\ |m_{I_0,j}(\mathbf{x}) - m_{I_1,j}(\mathbf{x})| - \frac{\varepsilon}{2}, & \text{otherwise} \end{cases} \quad (3)$$

where the linear and quadratic regions are determined by the Huber threshold ε . Since the L^1 criterion penalizes large differences less than the L^2 penalty, the metric is also able to preserve edges in images.

2.3. Diffeomorphic Demons Alternating Optimization

The method estimates flows $\phi_i(\mathbf{x}, t)$ of time-dependent velocity fields:

$$\phi_i(\mathbf{x}, t) = \phi_i(\mathbf{x}, 0.5) + \int_0^{(-1)^i(0.5-t)} \mathbf{v}_i(\phi_i(\mathbf{x}, 0.5 - (-1)^i\tau), 0.5 - (-1)^i\tau) d\tau \quad (4)$$

where i is 0 or 1. Since the diffeomorphisms $\phi_i(\mathbf{x}, t)$ are defined for different time points – $\phi_0(\mathbf{x}, t)$ defined for $t \in [0, 0.5]$ and $\phi_1(\mathbf{x}, t)$ for $t \in [0.5, 1]$ – we define a new time point variable $t_j = (0.5 - (-1)^j\tau) \in [0, 1]$ for $\phi_j(\mathbf{x}, t_j)$ using pseudo-time $\tau \in [0, 0.5]$. The velocity fields $\mathbf{v}_j(t_j)$ are defined in the space V of smooth, compactly-supported vector fields with a norm $\|\mathbf{v}_j(t_j)\|_V = \|L\mathbf{v}_j(t_j)\|_2$ and a linear differential operator $L = (Id + a^2\nabla^2)$ for $a \in \mathbb{R}$. In this work, as described in (Reaungamornrat *et al* 2016a), $\phi_j(t_j)$ and $\mathbf{v}_j(t_j)$ at each time point are defined with respect to the Lagrangian frame defined in the domain of $I_{0.5}$. The geodesics of ϕ_j are energy minimizing paths with the geodesic shortest lengths (GLS) measured in terms of the minimizing energy:

$$\rho(\phi_i(0.5), \phi_i) = \inf_{\mathbf{v}_i} \sqrt{\int_0^{0.5} \|\mathbf{v}_i(0.5 - (-1)^i\tau)\|_V^2 d\tau} \quad (5)$$

with a boundary $\phi_i(\mathbf{x}, 0.5) = \mathbf{x}$, $\phi_0(\mathbf{x}, 0) = \mathbf{y}$, and $\phi_1(\mathbf{x}, 1) = \mathbf{z}$ for a point $\mathbf{x}$, $\mathbf{y}$, and $\mathbf{z}$ in the domains of $I_{0.5}$, I_0 , and I_1 , respectively. Since a similar number of optimization iterations is used in estimation of ϕ_j , the diffeomorphisms are subject to the GSL constraint:

$$\rho(\phi_0(0.5), \phi_0) = \rho(\phi_1(0.5), \phi_1). \quad (6)$$

The method employs the Demons alternating optimization (Vercauteren *et al* 2009) to simplify the estimation and enable approximation of various deformation models (e.g., fluid, elastic, and viscoelastic). The alternating optimization separates minimization of image misalignment from imposition of a smoothness prior and is enabled through use of intermediate diffeomorphisms η_j in the constrained energy minimization:

$$E = \inf_{\eta_i, \phi_i} \frac{1}{2} \left\{ \alpha_s^2 \int_{\mathbf{x} \in \Omega} S(\mathbf{m}_{I_0 \circ \eta_0}, \mathbf{m}_{I_1 \circ \eta_1}, \mathbf{x})^2 d\mathbf{x} + \alpha_p^2 \left(\|\nabla \phi_1^{-1}\|_2^2 + \|\nabla \phi_0^{-1}\|_2^2 \right) \right\} + \frac{\alpha_v^2}{2} (\rho(\phi_0^{-1}, \eta_0)^2 + \rho(\phi_0^{-1}, \eta_1)^2) \quad (7)$$

subject to $\phi_i(0.5) = \eta_i(0.5) = Id$, $\rho(\phi_0(0.5), \phi_0) = \rho(\phi_1(0.5), \phi_1)$, and $\phi_i \circ \phi_i^{-1} = Id$, where α_S , α_P and α_U are regularization parameters, $\rho(\phi_j^{-1}, \eta_i)$ for $i, j \in \{0, 1\}$ measures GSL between ϕ_j^{-1} and η_i and $\|\nabla \phi_j^{-1}\|_2^2$ approximates harmonic energy.

The alternating minimization starts with estimating η_i to maximize alignment of $m_{I_0 \circ \eta_0}$ and $m_{I_1 \circ \eta_1}$ by optimizing equation (7) using a Gauss-Newton (GN) method. In this step, ϕ_i are considered to be known constants (i.e., $\phi_i = Id$ for the first iteration in the first / coarsest multiresolution level). GN provides update fields u_i to increment η_i as

$\eta_i^k = (\phi_j^{k-1})^{-1} + (G_{\sigma_U} * u_i) \circ (\phi_j^{k-1})^{-1}$ where k is an iteration number and G_{σ_U} is a Gaussian kernel with width σ_U . Computation of u_i is parallelizable for each voxel as:

$$u_i(x) = \frac{-S(x) \nabla_i S(x)}{\alpha_U^2 / \alpha_S^2 + \|\nabla_i S(x)\|_2^2} \quad (8)$$

where $\alpha_S = 1/S(x)$ penalizes noise, α_U constrains $\|u_i(x)\|_2 \leq 1/2\alpha_U$, and $\nabla_i S$ are the first derivatives of S with respect to ϕ_i . (A full derivation is given in (Reaungamornrat *et al* 2016a).) In the second step, the method considers η_i as constants (i.e., estimated in the first step) and finds the optimal ϕ_j by imposing the smoothness and invertibility constraints sequentially. The smooth diffeomorphisms are Tikhonov regularized solutions of equation (7) which are approximated by $\phi_j^{-1} = G_{\sigma_D} * \eta_i$, where G_{σ_D} is a Gaussian kernel with width σ_D , and the optimal ϕ_j are inverses of ϕ_j^{-1} which are estimated by minimizing the residual $\|\phi_j \circ \phi_j^{-1} - Id\|_2^2$ using gradient descent optimization. The method alternates between these two steps and yields the final diffeomorphism $\psi = \phi_0 \circ \phi_1^{-1}$ mapping I_0 to I_1 .

2.4. An Asymmetric Variant of MIND Demons

A variant of the MIND Demons algorithm using an asymmetric energy formulation (instead of the symmetric one in equation (7)) was introduced in (Reaungamornrat *et al* 2016b). The asymmetric form offers the potential advantage of speed per iteration (bypassing recalculation of m_{I_1}) and estimates a deformation ψ yielding $m_{I_0 \circ \psi} \approx m_{I_1}$ via the energy minimization:

$$E_A = \inf_{\xi, \psi} \frac{1}{2} \left\{ \alpha_S^2 \int_{x \in \Omega} S(m_{I_0 \circ \xi}, m_{I_1}, x)^2 dx + \alpha_P^2 \|\nabla \psi\|_2^2 + \alpha_U^2 \|L(\psi - \xi)\|_2^2 \right\} \quad (9)$$

where ξ denotes an intermediate deformation using the Demons alternating optimization (Section 2.3). In this method, update fields u (estimated in the first optimization step) are computed in terms of the first derivatives ∇S with respect to ψ (equation (8)) and used to increment ξ as $\xi^k = \psi^{k-1} + (G_{\sigma_U} * u) \circ \psi^{k-1}$. Following that, given the estimated ξ , the optimal smooth ψ derived from Tikhonov regularization of equation (9) is $\psi = G_{\sigma_D} * \xi$.

Similar to MIND Demons, the alternating optimization is performed in a multiresolution scheme to improve robustness against undesirable local optima. MIND descriptors of I_1 are computed only once prior to optimization in each multiresolution level since I_1 is constant. MIND descriptors of I_0 , on the other hand, are recomputed at each optimization iteration for the estimated deformations applied to I_0 . The method was implemented as a custom ITK algorithm using cubic B-spline representations of I_0 and I_1 . The nominal parameter settings and convergence criteria were similar to those of the symmetric form.

3. EXPERIMENTAL METHODS

3.1. Performance of MIND Demons Variants

The performance of the symmetric and asymmetric MIND Demons implementations was evaluated using a pair of 3D MR and CT images of the cervical spine (figure 4(a)). The MR moving image I_0 was acquired according to a standard clinical protocol for 2D sagittal-slice acquisition on a 1.5T Signa HDxt (GE Healthcare, Milwaukee WI, USA) with in-plane voxel-spacing of 0.5 mm, slice thickness of 3 mm, flip angle of 90° , repetition time (T_R) of 3,500 ms, and echo time (T_E) of 114.2 ms. An average of two acquisitions was used to reduce image noise. The CT fixed image I_1 was acquired on a Somatom Definition (Siemens Healthcare, Erlangen, Germany) with a standard scan technique of 120 kVp and 221 mAs, reconstructed at $0.2 \times 0.2 \times 0.8 \text{ mm}^3$.

Both implementations used a four-level image pyramid with downsampling factors of [16, 8, 4, 2] voxels and Gaussian smoothing with kernel widths of [8, 4, 2, 1] voxels. For the asymmetric MIND Demons method, downsampling and smoothing were applied to I_1 . Otherwise, for the symmetric MIND Demons method in all studies presented here, downsampling was applied to $I_{0.5}$, and smoothing was applied to I_1 . (I_0 was kept at its inherent resolution). The parameter settings in both algorithms were similar to those established in (Reaungamornrat *et al* 2016a), including $\sigma_p = 0.5 \text{ mm}$, $t_p = 0.1$, $\epsilon = 0.005$, $\sigma_U = 5$ voxels, and $\sigma_D = 1$ voxel, and were applied in all of the studies reported below. Similarly, the convergence criteria employed in both variants were analogous to those detailed in (Reaungamornrat *et al* 2016a). Specifically, the methods reached convergence if the maximum normalized magnitude of $\nabla_p S$ was less than $10^{-\ell}$ (where ℓ is the multiresolution level number) or if the gradient of the Huber metric (equation (3)) with respect to an iteration number was less than 10^{-6} . Aside from the stopping criteria, both methods were implemented with a maximum number of iterations of (100) per multiresolution level (i.e., a total maximum of 400 iterations for the four-level image pyramid). Non-rigid registration was initialized using normalized MI (NMI) rigid registration.

Computational efficiency was measured both in terms of the total number of optimization iterations evaluated prior to convergence at the last level of the image pyramid as well as the computation time (run on a Dell Precision T7600 with two 2-GHz Intel Xeon processors and 32 GB RAM). Registration accuracy was quantitatively measured in terms of target registration error (TRE) defined as the Euclidean distance between corresponding target points in I_0 and I_1 after registration:

$$\text{TRE}(\mathbf{x}_0, \mathbf{x}_1; \boldsymbol{\psi}) = \|\mathbf{x}_0 - \boldsymbol{\psi}(\mathbf{x}_1)\|_2 \quad (10)$$

where $\mathbf{x}_0$ denotes a target point in I_0 , $\mathbf{x}_1$ represents a target point in I_1 , and $\boldsymbol{\psi}$ is the estimated deformation. Six target points were identified on unambiguous anatomical features (e.g., tips of spinous and transverse processes). For qualitative, visual evaluation of registration accuracy, the vertebrae were segmented in I_0 (manually) and in I_1 (by simple bone thresholding) and overlaid as surface renderings.

3.2. Sensitivity to Anisotropic Voxel-Size

Owing to the well-known trade-offs between acquisition time and image quality, clinical MR images are often acquired in 2D slice acquisition with strongly anisotropic voxel-size – e.g., in-plane voxel size of approximately $0.6 \times 0.6 \text{ mm}^2$ and slice thickness ranging $\sim 2.0 - 6.0 \text{ mm}$. Clinical CT images, on the other hand, typically have nearly isotropic voxel-size owing to relatively fast 3D imaging capability of a multi-detector CT system (approximately $0.5 \times 0.5 \text{ mm}^2$ in the axial plane $\times 0.5 - 2.0 \text{ mm}$ longitudinally). The sensitivity of MIND Demons to the strongly anisotropic spatial resolution of the (MR) I_0 image is therefore important to its applicability and performance in real clinical data. In the following studies, only the symmetric MIND Demons method was evaluated (since the comparison study - Sections 3.1 and 4.1 - showed it to outperform its asymmetric variant).

The sensitivity to anisotropic voxel-size was analyzed using an ovine spine encapsulated in an MR-CT compatible flexible plastic cylinder filled with polyvinyl alcohol (simulating soft-tissue) (Reaungamornrat *et al* 2016a). The phantom was imaged first with scoliotic curvature for a T_2 -weighted MR moving image I_0 , followed by a CT fixed image I_1 with the straightened spine (figure 3). The MR I_0 was acquired using 3D acquisition on a 1.5T Magnetom Avanto (Siemens Healthcare, Malvern PA, USA) with flip angle of 150° , $T_R = 1,000 \text{ ms}$, and $T_E = 131 \text{ ms}$, and reconstructed at $0.9 \times 0.9 \times 0.9 \text{ mm}^3$ with a size of $192 \times 384 \times 128$ voxels. To simulate the typical 2D sagittal-slice acquisition with anisotropic voxel size, I_0 was smoothed and downsampled in the through-slice direction using a windowed sinc kernel:

$$H_w[m] = \begin{cases} \omega[m - W/2] \text{sinc}[m - W/2], & 0 \leq m \leq W - 1 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

where the window width W is equal to a downsampling factor and the window function is $\omega[x] = \text{Cos}(\pi x/W)$. The sinc function window was chosen to better approximate thick-slice acquisition in MR via rect function Fourier domain aperture. Binning used downsampling factors ranging 1 – 11 voxels (in increments of 1) and gave a set of 11 MR I_0 images with the slice thickness varying from 0.9 – 9.9 mm (figure 3(a)). Such a broad range of slice thickness was selected in order to test performance at extremes (i.e., find where the algorithm might break down at very large slice thickness) and to cover the range of thickness investigated in previous work (Manjón *et al* 2010, Plenge *et al* 2013, Shi *et al* 2013, Jafari-

Khouzani 2014, Ahmadi and Salari 2015). The CT I_1 image was acquired on a Somatom Definition Flash (Siemens Healthcare, Erlangen, Germany) using a scan technique of 100 kVp and 291 mAs, and reconstructed at $0.6 \times 0.6 \times 0.8 \text{ mm}^3$ with a size of $256 \times 256 \times 312$ voxels (figure 3(b)).

The vertebrae in the full-resolution images were segmented for visual evaluation and target point definition (TRE calculation). Thirty-two target points were manually identified from tips of the spinous and transverse processes of the ovine spine. Aside from assessment of registration accuracy, effects of MR slice thickness on diffeomorphic properties of the estimated deformations were investigated using invertibility ($\mathcal{Q}$) and minimum Jacobian of determinant ($\mathcal{D}$). The invertibility $\mathcal{Q}$ measures a pairwise registration error:

$$\mathcal{Q}(\psi, \psi^{-1}; \mathbf{y}, \mathbf{z}) = \frac{1}{2} \{ \|(\psi \circ \psi^{-1})(\mathbf{y}) - \mathbf{y}\|_2 + \|(\psi^{-1} \circ \psi)(\mathbf{z}) - \mathbf{z}\|_2 \} \quad (12)$$

where $\mathbf{y}$ denotes a point in I_0 , $\mathbf{z}$ is a point in I_1 , ψ is an estimated deformation, and ψ^{-1} is its inverse. Equation (12) quantifies the consistency of the correspondences between two images in a similar manner to the inverse consistency constraint in (Christensen and Johnson 2001). Therefore, the closer $\mathcal{Q}$ to zero, the better the ability of ψ is to preserve anatomical morphology and to provide (nonzero) positive Jacobian determinants. The minimum Jacobian determinant $\mathcal{D}$ assesses singularity and ability to preserve topology and local orientation of a deformation using Jacobian determinants, $\mathfrak{J}(\mathbf{x}) = \det(D_{\mathbf{x}}\psi(\mathbf{x}))$ for $\mathbf{x} \in \Omega$, where $D_{\mathbf{x}}\psi(\mathbf{x})$ is a spatial Jacobian of the deformation. The deformation is invertible if $\mathfrak{J}(\mathbf{x}) \neq 0$ and preserves topology and local orientation if $\mathfrak{J}(\mathbf{x}) > 0$. The minimum Jacobian determinant:

$$\mathcal{D}(\mathbf{x}; \psi) = \min_{\mathbf{x} \in \Omega_V} \{ \mathfrak{J}(\mathbf{x}) \} \quad (13)$$

was computed using a moving window Ω_V of 11^n voxels.

The sensitivity of MIND Demons to MR slice thickness was analyzed in comparison to that of a free-form deformation (FFD) method using local MI (LMI), referred to as LMI FFD, (Klein *et al* 2008) using TRE, $\mathcal{Q}$, and $\mathcal{D}$. The parameter settings for each method were established as described previously (Reaungamornrat *et al* 2016a), with the finest control-point spacing for LMI FFD set to 13 mm, the step size for the adaptive stochastic gradient descent (ASGD) optimization algorithm (Klein *et al* 2009) set to 340, and the number of histogram bins and the subvolume side-length used in computing LMI set to 96 bins and 150 mm, respectively. The three-level morphological pyramid in the MIND Demons method was constructed with downsampling factors of [8, 4, 2] voxels and Gaussian smoothing with kernel widths of [4, 2, 1] voxels. For LMI FFD, the multiresolution pyramid was constructed using only Gaussian smoothing without downsampling, and the smoothing was applied to both I_0 and I_1 since this scheme yielded the best registration accuracy. The convergence criteria implemented in MIND Demons were similar to those used in the previous study with a maximum number of iterations (100) per image-pyramid level. Since no additional

convergence criteria were implemented in LMI FFD, the method only stopped when ASGD reached the maximum number of iterations (100) in each level of the morphological pyramid. Both the LMI FFD and MIND Demons methods were initialized using NMI rigid registration.

3.3 Registration Performance in Clinical Studies

The registration performance of MIND Demons was validated and compared to LMI FFD in an institutional review board (IRB) approved retrospective clinical study. The study used 15 pairs of T_2 -weighted MR and CT images acquired for 15 patients undergoing spinal intervention at our institution—five image-pairs each for the cervical, thoracic, and lumbar spine. The time between acquisition of the MR and CT image pairs varied from 1 day to 5 years. The images exhibit typical variations in imaging protocol and image quality as summarized in table 1 ordered according to a patient ID (PID). The T_2 -weighted MR moving images I_0 were acquired with 2D sagittal-slice acquisition using a spine-echo pulse sequence, and the number of acquisitions averaged to reduce noise varied from 1 – 3. The MR images were reconstructed with in-plane spacing ranging 0.4 – 1.0 mm and slice thickness varied from 2.7 – 5 mm. The CT fixed images I_1 were acquired using scan techniques also presented in table 1, reconstructed with in-plane spacing varied from 0.2 – 0.5 mm and slice thickness ranging 0.6 – 1.3 mm. Figure 4 shows example MR and CT images of the cervical, thoracic, and lumbar spine.

Registrations performed using MIND Demons and LMI FFD were initialized by NMI rigid registration and used four-level image pyramids. The image pyramids for MIND Demons were constructed using downsampling factors of [16, 8, 4, 2] voxels and Gaussian smoothing with kernel widths of [8, 4, 2, 1] voxels, while those for LMI FFD were constructed using only Gaussian smoothing. Both methods were implemented using the stopping criteria as described in Section 3.2.

For assessment of registration accuracy, the vertebrae in the MR and CT images were segmented as described in Section 3.1. Target points for TRE measurement were manually identified based on unambiguous bone landmarks on the spine covering a broad range of the image volumes and covering multiple vertebral levels. Anatomical features of interest included: posterior-most aspect of the spinous process; inferior-most aspect of the spinous process; most lateral point of the transverse process; and tip of the odontoid process. Between 5 – 17 corresponding points were identified for each image pair, detailed as follows. For cases involving the cervical spine, we selected: (PID #1) 12 points across 10 vertebral levels; (PID #2) 9 points across 7 vertebral levels; (PID #3) 9 points across 9 vertebral levels; (PID #4) 5 points across 8 vertebral levels; and (PID #5) 6 points across 8 vertebral levels. For cases involving the thoracic spine, we selected: (PID #6) 7 points across 8 vertebral levels; (PID #7) 15 points across 12 vertebral levels; (PID #8) 9 points across 9 vertebral levels; (PID #9) 16 points across 8 vertebral levels; and (PID #10) 8 points across 8 vertebral levels. Finally, for cases involving the lumbar spine, we selected: (PID #11) 11 points across 8 vertebral levels; (PID #12) 8 points across 7 vertebral levels; (PID #13) 8 points across 6 vertebral levels; (PID #14) 7 points across 7 vertebral levels; and (PID #15) 8 points across 8 vertebral levels. To evaluate the reproducibility in target point selection, we

randomly selected 6 target points from randomly selected MR and CT images and evaluated variability for a single observer selecting each target point 5 times in separate trials. The overall reproducibility in target point selection was 0.8 ± 0.5 mm in MR images [median $\pm$ interquartile range (IQR)] and 0.4 ± 0.3 mm in CT images.

Normalized pointwise MI (NPMI) was additionally used to assess similarity between I_0 and I_1 after registration. NPMI quantifies the statistical dependence between a pair of intensities (i_I, i_J) , where i_I denotes an intensity in image I and i_J represents a corresponding intensity in image J by estimating the deviation of the actual joint probability from the expected one if the two intensities are independent (Bouma 2009, Fan *et al* 2012):

$$\text{NPMI}(i_I, i_J) = \frac{\log p(i_I)p(i_J)}{\log p(i_I, i_J)} - 1 \quad (14)$$

NPMI is bounded in the range $[-1, 1]$, and $\text{NPMI}(i_I, i_J) > 0$ if i_I and i_J are dependent. The diffeomorphic properties of the estimated deformations were measured using $\mathcal{Q}$ and $\mathcal{D}$ described in Section 3.2.

4. RESULTS

4.1. Performance of MIND Demons Variants

Figure 5 summarizes the performance of the symmetric and asymmetric MIND Demons variants. Both were initialized with a rigid transformation resulting in initial TRE [median $\pm$ IQR] equal to 6.1 ± 1.9 mm. MIND Demons converged with fewer iterations than its asymmetric variant – specifically, 243 iterations for MIND Demons compared to 312 for the asymmetric form. The MIND Demons method attained faster convergence characteristics owing to the more stable energy minimization (incorporating various priors) in equation (7) and estimation of two (smaller) symmetric diffeomorphisms instead of one large deformation (i.e., solving for ϕ_0 and ϕ_1 instead of ψ). However, as described in Section 2, the computation cost per iteration of MIND Demons was higher due to the estimation of two deformations ϕ_0 and ϕ_1 and recalculation of MIND descriptors for I_1 at each iteration. The computation time of the symmetric and asymmetric forms were 317.4 and 46.2 mins, respectively. The runtime of the MIND Demons algorithm can, however, be improved using distributed and/or parallel computing, since computation of ϕ_0 and ϕ_1 is independent. In addition, calculation of u_i for $i = 0$ and 1 in equation (8) as well as calculation of the MIND descriptors for each voxel can be computed in parallel. Adjustment of the convergence criteria could also potentially improve runtime.

Figures 5(b – e) show I_0 after Demons registration using semi-opaque surface rendering of the cyan I_1 and the pink (transformed) I_0 and superposition of yellow CT Canny edges on the (transformed) I_0 . Misalignment of the bone edges depicted in figures 5(b, c) and the zoomed-regions (1, 2) demonstrate the sensitivity of asymmetric MIND Demons to undesirable local optima. On the other hand, owing to the better constrained solution space (i.e., from the priors incorporated in the energy minimization), MIND Demons accurately aligned I_0 and I_1 (figures 5(d, e) and the zoomed-regions (3, 4)) with $\text{TRE} = 1.3 \pm 0.8$ mm

compared to $TRE = 3.6 \pm 4.4$ mm for the asymmetric method. The symmetric energy formulation in MIND Demons (equation (7)) therefore improved robustness against undesirable local optima and overall ability to resolve deformation to a level comparable to or better than the voxel-size.

4.2. Sensitivity to Anisotropic Voxel-Size

Figures 6 – 8 summarize the sensitivity of the LMI FFD and MIND Demons registration methods to MR slice thickness. As shown in Fig. 6, NMI rigid registration aligned the images with $TRE \approx 4.8 \pm 1.7$ mm irrespective of voxel size. LMI FFD yielded $TRE = 3.2 \pm 2.6$ mm for the thinnest MR slices (0.9 mm), and performance degraded to $TRE > 4$ mm for thicker MR slices. The MIND Demons method yielded better performance overall and reduced sensitivity to MR slice thickness, with $TRE = 1.3 \pm 0.8$ mm at 0.9 mm slice thickness, increasing to $TRE = 2.9 \pm 1.1$ mm for the largest (9.9 mm) slice thickness. The improvement over LMI FFD was statistically significant ($p < 0.05$) for all cases.

Figure 7(a) shows the mean invertibility for MIND Demons registration as a function of MR slice thickness. ($\mathcal{Q}$ was not evaluated for LMI FFD, since it only returns a forward map from I_0 to I_1 .) The MIND Demons method maintained invertibility across a broad range of slice thickness (0.9 – 8.1 mm), further substantiating its robustness against anisotropic resolution characteristics. Figure 7(b) shows that $\min \mathcal{D}$ for both methods increased with slice thickness but was lower overall for MIND Demons.

Figure 8 shows the (transformed) MR I_0 with slice thickness of 0.9 mm and 9.9 mm after LMI FFD and MIND Demons registration on the top and bottom rows, respectively, using semi-opaque surface rendering of the cyan CT I_1 and the pink (transformed) MR I_0 as well as superposition of yellow Canny edges of I_1 on the gray I_0 . Green arrows mark misalignment and/or unrealistic distortion of tissue introduced by LMI FFD. Misalignment in the most inferior vertebrae for both methods was due to motions estimated to correct large discrepancy in soft-tissue outweighing motions of vertebrae. Overall, and consistent with measurements in figures 6 – 7, MIND Demons resolved deformation well without unrealistic tissue folding / tearing effects.

4.3. Registration Performance in Clinical Studies

The performance of each registration method in clinical MR and CT images is summarized in figures 9 – 11. In each case, MIND Demons yielded improved registration accuracy in comparison to LMI FFD with accuracy comparable to or better than the voxel size. As illustrated in figure 9 for the cervical spine, the TRE after NMI rigid, LMI FFD, and MIND Demons registration was 4.3 ± 3.2 mm, 1.8 ± 1.2 mm, and 1.4 ± 0.8 mm, respectively. In the same order, TRE in the thoracic spine was 4.2 ± 2.6 mm, 2.5 ± 1.3 mm, and 1.6 ± 1.1 mm, and TRE in the lumbar spine was 4.2 ± 2.3 mm, 2.3 ± 1.6 mm, and 1.8 ± 1.1 mm. Pooling all cases, $TRE = 4.3 \pm 2.7$ mm after rigid alignment was reduced to 2.2 ± 1.4 mm for LMI FFD registration and 1.6 ± 1.0 mm for MIND Demons registration. The improvement of MIND Demons over NMI rigid and LMI FFD was statistically significant ($p < 0.001$ and $p < 0.02$, respectively) in each case. Neither LMI FFD nor MIND Demons appeared to introduce unrealistic distortion to anatomical structures, achieving $\min \mathcal{D} = 0.4$ and 0.3 , respectively.

The viscoelastic deformation estimated by MIND Demons was found to be diffeomorphic with $\mathcal{Q} = 0.001 \pm 0.001$ mm (max $\mathcal{Q} = 0.1$ mm).

The visual quality of registered images is illustrated in figure 10 with zoomed-in regions revealing the extent of estimated motion and improved image alignment achieved by MIND Demons compared to LMI FFD. Rigid initialization was estimated using the entire region of each images and therefore can be biased toward maximizing alignment of soft-tissue. The rigid initialization could be improved (not shown here for brevity) by limiting to a narrow bounded region around the vertebrae. The approach improved the rigid initialization of the spine but resulted in a large initial discrepancy in soft-tissue and could cause unrealistic distortion of the vertebrae after non-rigid registration. In that case, incorporation of a rigidity constraint (e.g., regularization based on orthogonality of spatial Jacobians of transformations of voxels belonging to bone (Reaungamornrat *et al* 2014)) could prevent such unrealistic distortion and yield further improvement in accuracy.

Figure 11 shows the NPMI following MIND Demons registration, further characterizing the improvement in local structural alignment following deformable registration. The NMPI images for the LMI FFD method are not shown in figure 11 for reasons of brevity and because NPMI (i.e., as a figure of merit) is biased in relation to the LMI objective function; however, the performance of LMI FFD is as shown by the TRE results of figure 9 and the image overlays of figure 10. The NPMI maps in figure 11 suggest a high level of image noise in the lumbar spine images, which diminished NPMI values for both NMI rigid and MIND Demons registration, but the MIND Demons method improved image alignment and NPMI for all spinal regions.

6. DISCUSSION and CONCLUSIONS

A symmetric, diffeomorphic MIND Demons method has been developed to compute viscoelastic transformations for MR-to-CT image registration. The algorithm incorporates MIND descriptors for modality-insensitive image representations, the Huber metric for robust estimation, and the Demons alternating optimization for simple numerical approximation of the viscoelastic diffeomorphism. The method demonstrated reduced sensitivity to strongly anisotropic voxel size in MR, with median TRE ranging 1.3 – 2.9 mm for MR slice thickness varied from 0.9 – 9.9 mm. The MIND Demons method was able to resolve deformation in MR with a large slice thickness in large part because the computation was performed with respect to the domain of $I_{0.5}$ defined in accordance with the spatial domain of nearly isotropic, fine-resolution I_1 (i.e., permitting TRE less than MR voxel size), and the image pyramid scheme adopted for MIND Demons did not include an additional smoothing kernel for I_0 (i.e., optimization in each pyramid level was performed using the original I_0).

Clinical studies demonstrated the robustness of the method against noise and intensity distortion in clinical MR and CT images, insensitivity to parameter settings (i.e., similar nominal parameter settings (Reaungamornrat *et al* 2016a) for all studies), and the ability to resolve deformations induced by variations in patient positioning with sub-voxel median TRE < 2 mm which is within the range (1 – 3 mm) desirable for spinal surgery (Cleary *et al*

2000, Shahidi *et al* 2001). The estimated deformation was diffeomorphic ($\mathcal{Q} = 0.001$ mm and $\min \mathcal{D} = 0.3$) and maintained tissue topology, yielded realistic smooth curvature of the spine, and captured coherent motion of surrounding soft-tissue.

The MIND descriptor used in this work is a variant of a self-similarity descriptor used in computer vision for object detection and image retrieval (Shechtman and Irani 2007). It was automatically computed for each voxel in an image without identification of feature points. Other descriptors have been used widely for 2D image matching – for example, Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) (Sargent *et al* 2009, Wang *et al* 2010, Lukashevich *et al* 2011). Furthermore, (Cheung and Hamarneh 2007) extended SIFT to N-dimensional (N-SIFT) and used it to estimate rigid alignment between MR brain images and CT cardiac images. 3D SURF (Brehler *et al* 2016) was used in atlas-based registration to estimate a similarity transformation to automatically adjust the standard planes of C-arm CBCT images of the calcaneus to improve visualization and facilitate intraoperative assessment of intra-articular fracture reduction. The performance of SIFT and SURF depends on identification of feature points and their correspondences. Medical images may challenge reliable detection of such feature points (Allaire *et al* 2008) due, for example, to high dimensionality, anisotropic resolution, noise, and artifacts. Memory and runtime requirement of SIFT- and SURF-based approaches also may limit their broad application. For example, 3D-SIFT-Flow estimating optical flows between $512 \times 512 \times 256$ CT images of the liver required 24 GB memory to store SIFT features of the two CT images (Xu *et al* 2016). In addition, since both descriptors are constructed based on directions of image gradients, they are not directly applicable to multimodality image registration (i.e., gradient directions of distinct modality images at corresponding points can be either same or opposite). Modality-insensitive variants of both descriptors (Chen and Tian 2009, Hossain *et al* 2011, Zhao *et al* 2014), however, are still challenged by computational complexity and sensitivity to feature point detection.

The Huber distance metric was used to reduce sensitivity to non-correspondent MIND descriptors (e.g., capturing different local structures due to image misalignment) and improve reliability and stability of the estimated deformation. A map measuring the saliency of points in an image (e.g., from local variances and structures (Zheng *et al* 2011) or local image features (Pimenov 2009)) can additionally be used to suppress the contribution of unreliable MIND descriptors (e.g., those computed in homogenous regions) and improve reliability and repeatability of the method. Application of the method to registration of preoperative MR images and intraoperative CBCT images is the subject of future work. Translation to a more clinically practical implementation requires a better distributed and/or parallelized computation framework to reduce computation time. A deformation-invariant descriptor could also be used to reduce computation steps and potentially improve runtime. Future work also includes analysis of sensitivity to noise and artifacts and addition of other forms of prior knowledge, such as rigidity of the vertebrae (Reaungamornrat *et al* 2014) to reduce unrealistic distortion of bone anatomy within otherwise free-form registration.

Acknowledgments

This work was supported in part by the National Institutes of Health grant number R01-EB-017226, collaboration with Siemens Healthcare XP, and the Thai Royal Government Scholarship. Dr. Adam Wang (Biomedical Engineering, Johns Hopkins University) and Dr. Amir Pourmorteza (Biomedical Engineering, Johns Hopkins University) are gratefully acknowledged for assistance with the MR scans.

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Figure 1.
Flow diagram of the MIND Demons algorithm.

Figure 2. MIND stencil configuration. (a) The stencil consists of 28 points arranged in a symmetric pattern spanning a cube of $5 \times 5 \times 5$ voxels in the CT image I_1 . (b) Adjacent slices of the 3D stencil are similar for axial, coronal, and sagittal planes. Gray circles mark voxels in the stencil, and the black circle marks the voxel for which MIND is computed.

Figure 3. Ovine spine phantom for evaluation of sensitivity to anisotropic spatial resolution in the MR image. (a) T_2 -weighted MR (I_0) images with the scoliotic spine at a slice thickness of 0.9 mm, 5.4 mm, and 9.9 mm, respectively, and its surface rendering showing 32 target points. (b) Corresponding CT (I_1) image with the spine straightened.

Figure 4. Example MR and CT images used in the clinical study. (a) Sagittal slices of T_2 -weighted MR (I_0) and CT (I_1) images of the cervical spine. (b) The same, in the thoracic spine. (c) The same, in the lumbar spine.

Figure 5.

Registration performance for asymmetric and symmetric variants of the MIND Demons method. (a) Distribution of TRE, showing median, IQR, and range. (b, d) Semi-opaque surface rendering of the cyan CT I_1 and the pink MR I_0 after asymmetric MIND Demons and MIND Demons registration. Cyan spheres mark the target points in I_1 , and yellow lines mark distances between corresponding target points in I_1 and I_0 after registration. (c, e) Superposition of yellow Canny edges of I_1 on the gray I_0 after asymmetric MIND Demons and MIND Demons registration. (1, 3) Zoomed-in regions of the surface overlays marked by the corresponding green rectangles. (2, 4) Zoomed-in regions of the Canny-edge overlaid images marked by the corresponding green rectangles.

Figure 6. Sensitivity of registration performance to MR anisotropic voxel-size. TRE resulting from registration of MR and CT images using (a) NMI rigid, (b) LMI FFD, and (c) MIND Demons registration.

Figure 7. Sensitivity of registration performance to MR anisotropic voxel-size. (a) Mean $\mathcal{Q}$ and (b) $\min \mathcal{D}$ evaluated as a function of slice thickness.

Figure 8.

MR-CT registration with anisotropic voxel-size in the MR moving image. From left to right: semi-opaque surface overlay of the cyan CT fixed image I_1 and the pink MR moving image I_0 after registration and superposition of yellow Canny edges of I_1 and the gray I_0 after registration with MR slice thickness of 0.9 mm and 9.9 mm, respectively. From top to bottom: registration results after LMI FFD and MIND Demons registration. Cyan spheres on the surface overlays are target points in I_1 , and yellow line segments mark distances between corresponding target points in I_1 and I_0 after registration. Green arrows mark regions

misaligned or unrealistically distorted by LMI FFD compared to the corresponding regions estimated by MIND Demons.

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Figure 9. Registration performance in MR-to-CT registration. The box plots show TRE distributions measured in five image pairs for each spinal region (cervical, thoracic, and lumbar) across 15 patients.

Figure 10.

MR-to-CT registration performance in clinical studies: (Top) cervical spine; (Middle) thoracic spine; and (Bottom) lumbar spine. Each case shows the registration results for an exemplary case for NMI rigid, LMI FFD, and MIND Demons registration. Semi-opaque surface renderings show the CT fixed image I_1 in cyan and the MR moving image I_0 in pink along with zoomed-in regions marked by green rectangles. Also shown are Canny edges of I_1 (yellow) overlaid on the I_0 (gray) after registration.

Figure 11. NPMI in images following (top) NMI rigid and (bottom) MIND Demons registration of MR and CT images in the cervical, thoracic, and lumbar spine.

Table 1

Image Acquisition Techniques and Reconstruction Parameters for Clinical Studies

Patient ID (PID)	MR				CT		
	flip angle (°)	T _R (ms)	T _E (ms)	voxel size (mm ³)	kVp	mAs	voxel size (mm ³)
1	90	3,650	118	(0.4×0.4×3.5) <i>M1</i>	120	108	(0.3×0.3×1.3) <i>C1</i>
2	90	2,000	100	(0.4×0.4×3.3) <i>M2</i>	120	226	(0.2×0.2×0.8) <i>C2</i>
Cervical	90	2,500	138	(0.4×0.4×3.5) <i>M1</i>	120	199	(0.2×0.2×1.3) <i>C3</i>
4	90	3,800	110	(0.8×0.8×4.0) <i>M3</i>	120	279	(0.3×0.3×0.8) <i>C2</i>
5	90	3,500	114	(0.5×0.5×3.0) <i>M4</i>	120	221	(0.2×0.2×0.8) <i>C2</i>
6	90	5,400	120	(0.7×0.7×3.4) <i>M5</i>	140	165	(0.4×0.4×0.8) <i>C4</i>
7	160	3,000	92	(0.8×0.8×3.0) <i>M6</i>	140	248	(0.3×0.3×0.8) <i>C4</i>
Thoracic	162	2,500	96	(1.0×1.0×3.5) <i>M7</i>	140	422	(0.4×0.4×0.6) <i>C3</i>
9	90	3,217	948	(0.7×0.7×4.5) <i>M8</i>	140	235	(0.3×0.3×0.8) <i>C4</i>
10	90	5,167	105	(0.7×0.7×2.7) <i>M9</i>	120	186	(0.5×0.5×0.8) <i>C2</i>
11	150	4,220	103	(0.6×0.6×3.3) <i>M7</i>	140	80	(0.3×0.3×0.8) <i>C4</i>
12	90	5,700	109	(0.5×0.5×4.0) <i>M4</i>	120	233	(0.3×0.3×0.8) <i>C5</i>
Lumbar	131	2,000	103	(0.8×0.8×3.0) <i>M6</i>	140	147	(0.3×0.3×0.8) <i>C4</i>
14	90	3,200	110	(0.5×0.5×5.0) <i>M4</i>	120	326	(0.3×0.3×0.8) <i>C2</i>
15	144	4,220	103	(0.6×0.6×3.3) <i>M7</i>	140	75	(0.3×0.3×0.8) <i>C4</i>

M1 3T Signa HDxt (GE Healthcare, Milwaukee WI, USA),

M2 1.5T Achieva (Philips Healthcare, Amsterdam, Netherlands),

M3 0.3T OpArt (Toshiba Corporation, Tokyo, Japan),

M4 1.5T Signa HDxt (GE Healthcare, Milwaukee WI, USA),

M5 1.5T Vantage Titan (Toshiba Corporation, Tokyo, Japan),

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- M6* 3T Skyra (Siemens Healthcare, Erlangen, Germany),
M7 1.5T Aera (Siemens Healthcare, Erlangen, Germany),
M8 1.5T Signa Excite (GE Healthcare, Milwaukee WI, USA),
M9 1.5T Genesis Signa (GE Healthcare, Milwaukee WI, USA),
C1 LightSpeed Ultra (GE Healthcare, Milwaukee WI, USA),
C2 Somatom Definition (Siemens Healthcare, Erlangen, Germany),
C3 LightSpeed VCT (GE Healthcare, Milwaukee WI, USA),
C4 Somatom Definition Flash (Siemens Healthcare, Erlangen, Germany),
C5 Sensation 16 (Siemens Healthcare, Erlangen, Germany).