MRI Composing for Whole Body Imaging

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Abstract. Whole-body magnetic resonance imaging is an emerging application gaining vast clinical interest during the last years. Although recent technological advances shortened the longish acquisition time, this is still the limiting factor avoiding its wide-spread clinical usage. The acquisition of images with large field-of-view helps to relieve this drawback, but leads to significantly distorted images. In this paper, a novel scheme for MRI composing is presented. The approach is based on simultaneous registration of two MRI volumes to their linear weighted average. The method successfully compensates for the distortions and allows to generate high-resolution whole body images. Results on several in-vivo data sets are presented.

1 Introduction

Whole-body (WB) magnetic resonance imaging (MRI) is becoming a popular clinical tool due to the recent technological advances in MRI, making faster acquisitions possible. Unlike computed tomography (CT), the acquisition of high-resolution MR images is not feasible during continuous table movement, making a multi-station scanning necessary to cover larger body regions. The compounding of the partially overlapping volumes is straightforward, since the MR scanner keeps track of their exact spatial locations.

The creation of WB images further increases the number of clinical applications for MRI, so far reserved for other modalities. From a current perspective, the major disadvantage using MRI for WB imaging in comparison to CT is the longer scanning time. In this report, we use MR acquisitions with a large field-of-view (FOV), enabling to cover with the same number of scans larger parts of the body. This, however, leads to a degradation of the images by geometrical distortion artefacts towards the boundaries, further described in [1, 2]. We propose a novel method, originating from the field of brain atlas construction, to correct for the geometrical distortion in the overlapping area (Sect. 2). Our experiments show the good results on in-vivo data (Sect. 3).

2 Method

In order to introduce our approach of deformable composing recently proposed [3], we define the two volumes to be stitched as $I_1 : \Omega_1 \subset \mathbb{R}^3 \to \mathbb{R}$ and $I_2 : \Omega_2 \subset \mathbb{R}^3 \to \mathbb{R}$. The overlapping domain is denoted as $\Omega_o = \Omega_1 \cap \Omega_2$. Since the overlap Ω_o is the only part where the two images share any information, a naive approach for the composing could be defined as a minimization problem with respect to a certain distance/similarity measure $\rho(\cdot)$, or

$$\hat{\mathcal{T}}_{1,2} = \arg\min_{\mathcal{T}_{1,2}} \int_{\Omega_o} \rho(I_1(\mathcal{T}_1(\mathbf{x})) - I_2(\mathcal{T}_2(\mathbf{x})))d\mathbf{x} \tag{1}$$

where $\mathbf{x} = (x, y, z)$ denotes a voxel position, and $\mathcal{T}_{1,2}$ are the parameters of the transformations $\mathcal{T}_1$ and $\mathcal{T}_2$ relating the two volumes in the spatial domain. The most common approach in pairwise registration is to assume that one of the two transformations is equal to the identity transformation. In our case, such an approach would lead to several problems: (i) through the selection of a moving and a fixed image, we would introduce a certain bias on the registration result, (ii) since both volumes are distorted due to the inhomogeneous magnetic field in the overlap volume, none of them is actually representing a good reference frame, and (iii) a registration performed only within the overlap may result in discontinuities with respect to the rest of the volumes. In order to overcome these problems, we propose an iterative simultaneous registration using a *linear weighted average*. The idea of the weighted average is to account for the underlying physical properties of increasing distortions towards the volume boundaries. Assuming that the boundary information is less reliable, we would like to reduce its influence to the registration.

2.1 Simultaneous registration to linear weighted average

Let us define another volume $S : \Omega_s$ on the union of the two volume domains $\Omega_s = \Omega_1 \cup \Omega_2$. The intensities of S are set using our average model, or

$$S(\mathbf{x}) = \begin{cases} f(\mathbf{x}), & \text{if } \mathbf{x} \in \Omega_o \\ I_1(\mathcal{T}_1(\mathbf{x})), & \text{if } \mathbf{x} \in \Omega_1 \setminus \Omega_2 \\ I_2(\mathcal{T}_2(\mathbf{x})), & \text{if } \mathbf{x} \in \Omega_2 \setminus \Omega_1 \end{cases} \tag{2}$$

where $f(\cdot)$ is a function computing the linear weighting in the overlap volume, or

$$f(\mathbf{x}) = (1 - h(\mathbf{x})) \cdot I_1(\mathcal{T}_1(\mathbf{x})) + h(\mathbf{x}) \cdot I_2(\mathcal{T}_2(\mathbf{x})). \tag{3}$$

The linear function $h(\cdot)$ has a range of $(0, 1)$ and is defined for the overlap domain Ω_o with respect to the composing direction. In our application, this direction is usually along the head-feet axis which corresponds to the y-axis of our common 3D coordinate system for all the MRI volumes.

The setup for the deformable composing and the initialization of the linear weighted average is illustrated in Fig. 1. We can reformulate the naive registration in Eq. 1 in order to pose a simultaneous registration based on the linear weighted average S. In terms of an energy function (which is to be minimized), we define

$$E_{\text{data}}(\mathcal{T}_{1,2}) = \sum_{i=1}^{2} \int_{\Omega_o} \rho(S(\mathbf{x}) - I_i(\mathcal{T}_i(\mathbf{x})))d\mathbf{x}. \tag{4}$$

In order to reduce the dimensionality of the problem, we consider Free Form Deformations as the transformation model for the two images. A deformation grid $G : [1, K] \times [1, L] \times [1, M]$ is superimposed onto the volume domain Ω_s. By deforming the grid (with a 3D displacement vector $\mathbf{d_p}$ for each control point) the underlying structures are aligned. The transformation of a voxel $\mathbf{x}$ can be expressed using a combination of basis functions, or

$$\mathcal{T}(\mathbf{x}) = \mathbf{x} + \mathcal{D}(\mathbf{x}) \quad \text{with} \quad \mathcal{D}(\mathbf{x}) = \sum_{\mathbf{p} \in G} \eta(|\mathbf{x} - \mathbf{p}|)\, \mathbf{d_p} \tag{5}$$

where $\eta(\cdot)$ is the weighting function (based on cubic B-Splines) measuring the contribution of the control point $\mathbf{p}$ to the displacement field $\mathcal{D}$.

Now, we can rewrite the objective function defined in Eq. 4 based on the two deformation grids G_1 and G_2, or

$$E_{\text{data}}(\mathcal{T}_{1,2}) = \sum_{i=1}^{2} \frac{1}{|G_i|} \sum_{\mathbf{p} \in G_i} \int_{\Omega_o} \hat{\eta}(|\mathbf{x} - \mathbf{p}|) \cdot \rho(S(\mathbf{x}) - I_i(\mathcal{T}_i(\mathbf{x})))d\mathbf{x}. \tag{6}$$

where $\hat{\eta}(\cdot)$ computes the influence of a voxel $\mathbf{x}$ to a control point $\mathbf{p}$. Such a function acts as a *projection* of the distance/similarity measure computed from the volume domain back to the coarser level of control points. Different definitions of the $\hat{\eta}(\cdot)$ have to be considered with respect to the used similarity measure. We use the normalized cross correlation (NCC) which is robust to intensity variations common in MRI. For statistical measures such as NCC, we define

$$\hat{\eta}(|\mathbf{x} - \mathbf{p}|) = \begin{cases} 1, & \text{if } \eta(|\mathbf{x} - \mathbf{p}|) > 0 \\ 0 & \text{otherwise} \end{cases}. \tag{7}$$

Basically, this function masks voxels influenced by a control point $\mathbf{p}$ resulting in a local image patch centered at the control point. From this patch, a *local* similarity measure can then be computed.

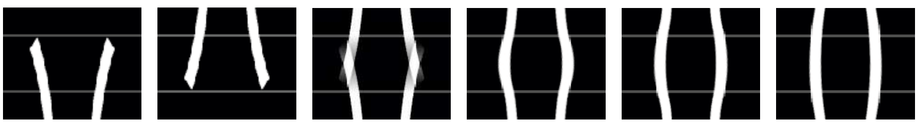

Fig. 1. Synthetic example of a deformable composing. The first and second image are to be composed where both are significantly distorted. The initialization of our linear weighted average is shown in the third image. The horizontal gray lines indicate the borders of the overlap area. Fourth to sixth image is an illustration of the registration progress and the iterative improvement of the linear weighted average.

The simultaneous registration to an average should overcome the problems for the reference selection, mentioned before. This is very similar to atlas construction approaches where the average is used as the reference image in order to achieve an unbiased coordinate frame (e.g. for shape models) [4]. In addition, we try to account for the increasing distortions using a linear weighted average. For optimization of the proposed method we make use of discrete framework for image registration presented [5].

3 Experimental validation

We evaluate our method on 8 whole-body T1- and T2-weighted data sets from three different Siemens MR scanners: Avanto 1.5T, Trio 3T, and Espree 1.5T. The overlaps vary between 5 and 27 cm. An example mosaic is shown in Fig. 2, consisting of three volumes having a FOV of $50 \times 50 \times 28$ cm^3, a resolution of $448 \times 448 \times 35$ voxels, and an overlap of 5 cm. The resolution for the final stitching is $448 \times 1256 \times 35$ where the computation of the two composings take together approximately 25 min. To illustrate that the proposed method also works for varying overlaps, we show the stitching of 3 volumes for whole-spine MR, see Fig. 3. The first overlap is with 15.2 cm very large and our method arrives at producing a sharper average. The second one, with only 1.4 cm,

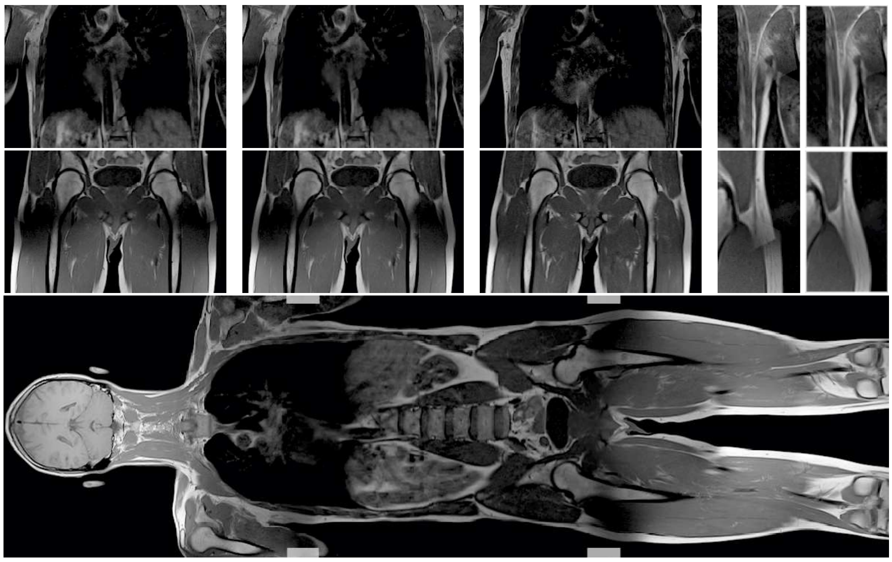

Fig. 2. Top from left to right: Initial average, final composing after 3 optimization cycles, reference scan where the overlap volume is centered within the MR scanner, and magnification of initialization and final composing. Our method is able to reproduce similar smooth and continuous transitions as present in the reference images. Bottom: Resulting whole body image after composing of all three stations.

Fig. 3. Composing of 3 spine volumes. Top: initial average. Bottom: result. Gray bars indicate overlap.

shows discontinuities in the initial average, which are removed after deformable composing.

4 Conclusion

Speeding up the acquisition for WB-MRI with large FOV images leads to significant distortions towards the boundaries. Methods for distortion correction proposed in the literature are not applicable to the WB imaging setup because they either elongate the workflow or only correct for specific system-induced distortions. We propose the usage of simultaneous deformable registration in a composing scenario, which has not yet been done before. Key for the simultaneous registration is the creation of a linear weighted average, each of the two images is registered to. Our experiments on synthetic and in-vivo data show the ability of the method to correct for distortions. The unaltered clinical workflow makes our approach very interesting for being integrated into further MR scanner generations.

References

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