DEFORMABLE REGISTRATION OF MR IMAGES USING A HIERARCHICAL PATCH BASED APPROACH WITH A NORMALIZED METRIC QUALITY MEASURE

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ABSTRACT

Magnitude Diffusion Weighted Magnetic Resonance Imaging (DW-MRI) is used to detect lesions in abdominal organs such as the liver. For diagnosis and interventional planning, DW-MRI needs to be registered with Magnetic Resonance (MRI) images in order to provide an anatomical context. DW-MRI usually generates images that contain large regions with only little image information. This makes it difficult to elastically register those images to images from other imaging modalities. In this work, we apply a deformable registration approach in order to register magnitude DW-MRI data with MRI images. A normalized quality measure is used to sort out local deformations in low image signal areas that cause non-plausible local deformations. An evaluation on 5 patients shows promising results.

Index Terms— Registration, diffusion weighted MR, metric assessment

1. INTRODUCTION

Magnitude Diffusion Weighted Magnetic Resonance Imaging (DW-MRI) is very well suited to distinguish tumors from surrounding tissue in the liver. Standard Magnetic Resonance Imaging (MRI) is applied in the same acquisition cycle to assess other structures like vessels which are not visible in DW-MRI. For diagnosis and operation planning, the DW-MRI has to be registered with the standard MRI data. Due to breathing and patient movement, deformable registration is needed. However, the DW-MRI include areas that contain very little or no information that can be used for registration. Therefore, standard deformable registration approaches often do not yield satisfactory results. Normalizing the input images in a preprocessing step [1, 2], e.g. to remove intensity differences from different states of contrast agent saturation can help to improve registration quality for images that do not differ much from each other. Stronger divergences can be solved by using registration methods based on features like landmarks [3], pre-segmented areas [4, 5] or vessels [6] that are detected in a preprocessing step. However, such features cannot be reliably detected in DW-MRI images due to the low resolution and weak image signal.

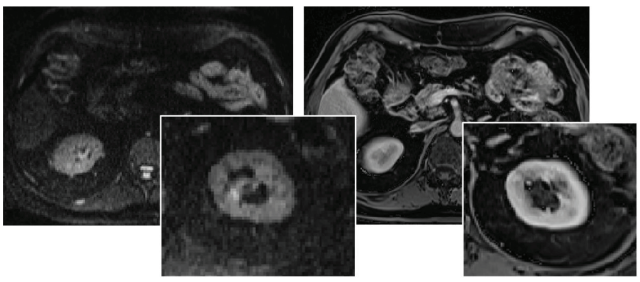
Our registration approach is based on the work of Söhn et al. [7]. They divide the image into small patches called featurelets and register them individually using rigid registration. Patches with a degenerated optimization minimum are sorted out based on eigenvalue analysis of the Hessian matrix at the optimum. This avoids a false deformation in homogeneous areas. However, the proposed registration scheme is only applied to structures with high contrast. In particular, it is applied to lung registration as well as head and neck registration problems. Furthermore, the benefit of sorting out degenerate metric optima in comparison to incorporating all metric optima is not evaluated. The contribution of our work is as follows. We first give a mathematical foundation and geometrical interpretation of the optima assessment which is missing in the original work in order to clarify why the eigenvalues of the local Hessian can be used as a metric quality measure (cf. Sec. 2). Secondly, we derive a single value for assessing the metric quality. This measure is used in a hierarchical patch based framework in order to solve the described registration task between MRI and DW-MRI volumes with weak image signal. The benefit of sorting out degenerated metric optima in this application scenario is demonstrated by comparing the registration results with and without discarding patches according to the metric quality (cf. Sec. 3).

2. REGISTRATION USING METRIC OPTIMA ASSESSMENT

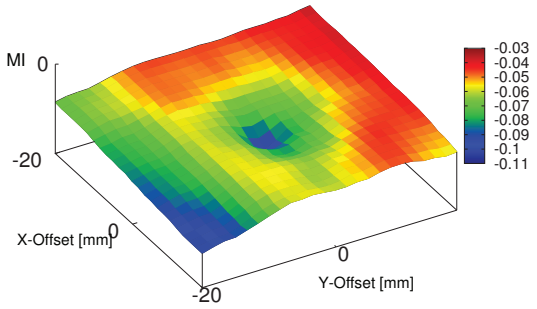
Intensity based image registration is typically carried out by minimizing an error metric $\Omega_{F,M} : \mathcal{R}^n \mapsto \mathcal{R}$, where F is the fixed image and M is the moving image that has been transformed by a transformation $T(\vec{X})$ characterized by the transformation parameters $\vec{X} \in \mathcal{R}^n$. Formally such a registration problem can be written as

$$\vec{X}^* = \underset{\forall \vec{X}}{argmin}\, \Omega_{F,M}\left(\vec{X}\right) . \tag{1}$$

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(a)



(b)

Fig. 1. (a) Magnitude image of diffusion weighted MRI (left) and MRI image (right). The zoomed areas are registered by shifting the image in x-/y-direction. (b) Mutual Information metric plot of the registration using exhaustive search within $\pm$ 20 mm bounds from the ideal registration position. The local minimum in the middle denotes this best position where both regions have an optimal fit. However the global minimum over the whole search space is found at the borders of the search space, which is far away from the optimal fit.

Once a local optimal transform parameter vector $\vec{X}^*$ is found, it is in some applications important to assess the quality of the found optimum, i.e. to know how successful the registration has been performed. Here, the global optimum of the metric is not necessarily the best solution, but a distinct local optimum. For example, the local minimum in the center of the plot in Fig. 1(b) corresponds to the optimal registration solution for the images shown in in Fig. 1(a) even though the minimum at the border of the plot has lower metric values. This example makes clear that using the metric value by itself is not a suitable registration quality criteria in this case. Instead the metric's shape around the local optimum needs to be assessed.

Söhn et al. [7] threshold the eigenvalues of the Hessian matrix at an optimum to assess its registration quality. In the following, we give a geometrical interpretation why the eigenvalues are suited to assess a registration optimum and derive a single scalar value as a generalized assessment measure.

Let $\vec{X}^* \in \mathcal{R}^n$ be registration transform parameters resulting in a local minimum of an error metric $\Omega : \mathcal{R}^n \mapsto \mathcal{R}$. The error metric shall be smooth at the point, i.e. having at least 3 continuous partial derivatives at every point in a neighborhood B around $\vec{X}^*$. The registration quality shall be assessed at that point in the parameter space.

According to Taylor's theorem the given error metric can be written as a polynomial of degree m plus a remainder R:

$$\Omega(\vec{X}) = \sum_{|\alpha|=0}^{m} \frac{1}{\alpha!} \frac{\partial^\alpha \Omega(\vec{X}^*)}{\partial \vec{X}^\alpha} \left(\vec{X} - \vec{X}^*\right)^\alpha + \sum_{|\alpha|=m+1} R_\alpha(\vec{X}) \left(\vec{X} - \vec{X}^*\right)^\alpha , \quad (2)$$

where α is a multi index. For the degree $m = 2$ this comes down to

$$\begin{aligned} \Omega(\vec{X}) = \Omega(\vec{X}^*) & \\ + \nabla\Omega(\vec{X}^*) \cdot \left(\vec{X} - \vec{X}^*\right) & \\ + \frac{1}{2} \left(\vec{X} - \vec{X}^*\right)^T H_\Omega(\vec{X}^*) \left(\vec{X} - \vec{X}^*\right) & \\ + \sum_{|\alpha|=3} R_\alpha(\vec{X}) \left(\vec{X} - \vec{X}^*\right)^\alpha , & \quad (3) \end{aligned}$$

where ∇ is the gradient operator and H_Ω is the Hessian matrix.

$\vec{X}^*$ being a local minimum, the metric's gradient is necessarily zero ($\nabla\Omega(\vec{X}^*) = \vec{0}$). Furthermore we assume the remainder to be zero as we are only interested in the behavior of the metric in a small area around $\vec{X}^*$. Incorporating those simplifications, (2) approximately becomes

$$\Omega(\vec{X}) \approx \Omega(\vec{X}^*) + \frac{1}{2} \left(\vec{X} - \vec{X}^*\right)^T H_\Omega(\vec{X}^*) \left(\vec{X} - \vec{X}^*\right). \quad (4)$$

For $n = 1$ this is a simple parabola at the point $\vec{X}^*$. In that 1d case the peakness p of the metric's approximation $\Omega(x) \approx \Omega(x^*) + \frac{1}{2}\Omega''(x^*)(x - x^*)^2$ can simply be expressed in terms of its second derivative at the local minimum which is inversely proportional to the opening angle of the fitted parabola:

$$p = |\Omega''(x^*)\,|. \quad (5)$$

The idea now is that the registration result is more reliable the stronger the peak at the minimum is and thus the larger p becomes.

Now, we are generalizing the procedure to arbitrary dimensions, i.e. we want a single scalar p expressing the peakness of the metric. Thereby, it is important that if the registration result is identified to be unreliable in a single direction the overall registration result shall be said to be unreliable. Imagine for example a 2d function that is shaped similar to a canyon. In that case, the minimum in the direction towards the canyon boundaries is very distinct, whereas the minimum along the

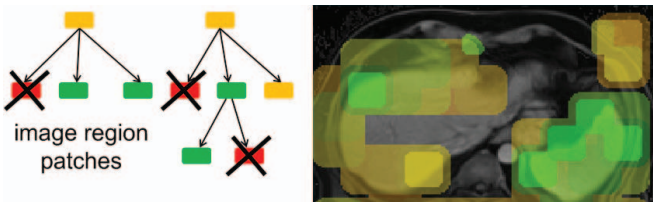


Fig. 2. Image patch hierarchy. Patches with a low metric peakness are sorted out.

canyon is not. It is clear that such a shape shall be assessed as a poor registration reliability. The just described behavior can be achieved by a multiplication of the peakness values in independent directions. Those independent directions can be found by eigendecomposition of the Hessian matrix H. Being symmetric, H can be written as

$$H = Q \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix} Q^T , \tag{6}$$

where λ_i are the eigenvalues and Q contains the normalized eigenvectors of H. Then p is given by the product of the eigenvalues:

$$p = \prod_{\forall i} \lambda_i = \det H . \tag{7}$$

Thus the peakness and thereby the registration quality of an error metric Ω at a local minimum x^* can be expressed by the determinant of Ω's Hessian matrix.

Similar to Söhn et al. [7], a patch based registration scheme is used for registration. Mutual Information [8] has been chosen as the metric. Instead of using a single grid, we use a hierarchy of patches of different sizes. Here, single patches are recursively divided until reasonable small patches are created. Each patch in each resolution is rigidly registered with the reference image and the peakness value as defined in (7) is computed. For every voxel, the transformation parameters of the patch with the highest peakness value is selected (cf. Fig. 2). In case the peakness value is lower than a threshold ϵ, the voxel does not get assigned transformation parameters. In this case, the transformation parameters for the voxel are estimated by means of interpolation as shown in [9, 10]. In order to avoid discontinuities during interpolation, areas with assigned transform parameters are eroded by a constant γ.

3. EVALUATION

For clinical evaluation, 10 datasets from 5 patients have been used. All patients had liver lesions that have been treated using radiofrequency ablation. 5 data sets were magnitude DW-MRI volumes (1.92 x 1.92 x 7.8 mm spacing) and 5 other were T1 or T2 weighted MRI volumes (1.25 x 1.25 x 4 mm spacing). The DW-MRI and MRI volumes were registered using the proposed approach. $\gamma = 1$ cm was used for eroding contacting transformation areas. Two patch resolution levels turned out to be sufficient in our tests (patch size 20% and 10% of image dimensions). Furthermore, a peakness threshold of $\epsilon = 10^{-7}$ was sufficient to sort out bad transforms. Fig. 3 shows an example of the registration of a magnitude DW-MRI with a T2-MRI volume using the proposed patch-based approach. The left image shows the deformation of a data set for a registration where regions have been sorted out according to their absolute metric value. The threshold for the metric has been chosen such that a minimum of distortions occur while having at least 5 patches in the body of the patient. However, strong distortions still occur in areas where the metric optimum of the corresponding patch is far away from the optimal position. This example makes clear that the absolute metric value is not a proper measure in this case. The middle-left image shows the same configuration, whereas the proposed peakness value is used for discarding patches. As it can be seen, no unnatural deformations occur. The last two images show the corresponding registration quality in a split view. The middle-right image shows the overlap of both volumes after acquisition and the right image shows the overlap after applying the proposed method. The registration quality is clearly improved over the whole image (arrows).
For quantitative evaluation, the liver has been segmented by medical experts in clinical MRI images. An artificial deformation field was created with an amount of deformation similar to the typical deformation as observed in clinical images. The deformation field was then applied to the MRI as well as to the segmentation mask. The MRI was also locally smoothly attenuated in order to simulate the effect of low-signal areas in DW-MRI. The resulting deformed and attenuated MRI were registered with the original MRI. The resulting transformation was then applied to the segmentation mask. Table 1 shows overlap error, volume difference, average surface distance, root mean square error and maximum surface distance (cf. [11] for a detailed description of the error measures, lower values are better) between the registered mask and the deformed mask created with the known deformation field. A comparison between the proposed method with and without discarding patches according to the proposed method is given. As can be seen, the registration quality is significantly improved by discarding patches in comparison to using all patches for deformation.

4. DISCUSSION AND CONCLUSION

In this work, a method to register magnitude DW-MRI data with MRI images is proposed. A normalized quality measure is used to sort out local deformations in low image signal areas that cause non-plausible local deformations. A patch-based hierarchical registration scheme is proposed to robustly

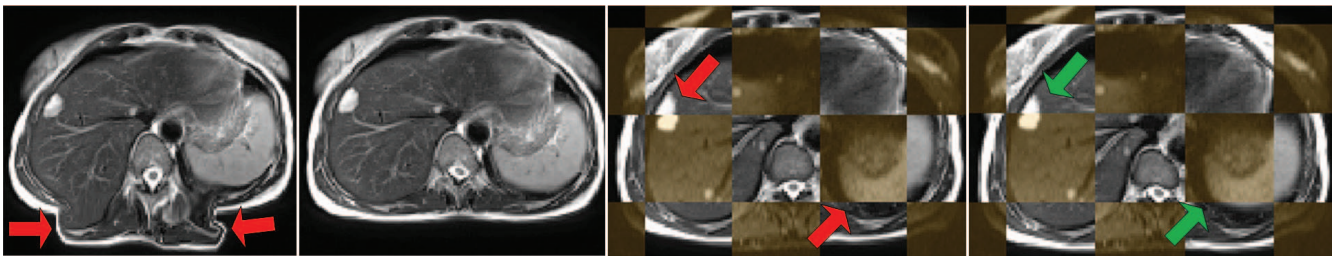


Fig. 3. From left to right: moving image deformation with discarding patches according to absolute metric value (left, arrows indicate non plausible deformations) and with discarding patches according to the peakness value (middle-left, plausible deformation). Split view of the registration before (middle-right) and after applying the proposed registration method (right, arrows indicate that the local fit has been significantly improved).

Table 1. Error measures (cf. [11]) are shown for the proposed method (with and without discarding bad patches).

Method	Overl. Err. [%]	Vol. Diff. [%]	Avg. Dist. [mm]	RMS Dist. [mm]	Max. Dist. [mm]
Discarding patches	8.21	1.02	0.86	1.59	8.94
All patches	17.41	7.23	2.31	4.77	32.94

register the image areas that contain relevant image information. Evaluation showed a clear improvement of the registration quality in comparison to deformable registration that incorporates the whole image information.

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