DEMONS REGISTRATION WITH LOCAL AFFINE ADAPTIVE REGULARIZATION: APPLICATION TO REGISTRATION OF ABDOMINAL STRUCTURES

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ABSTRACT

We present a local affine based adaptive regularization approach as an alternative to the homogeneous regularization used in Thirion’s demons non-rigid registration algorithm [1]. The original homogeneous regularization does not preserve the deformation field discontinuities that are related to the independent motion of different organs, as commonly occurs during CT and MR imaging of the abdomen and pelvis. Instead, our method fits local affine transformation to each voxel, identifies the discontinuities between the locally fitted affine transformations and adaptively smooths the deformation field, while preserving its local affine discontinuities. Experimental results on both synthetic and real CT images demonstrate that our method yields a smoother deformation field while preserving the registration accuracy.

Index Terms— Locally affine registration, Demons non-rigid registration, Adaptive regularization

1. INTRODUCTION

Abdominal image registration is a prerequisite task for atlas based abdominal image segmentation, which is utilized by many clinical applications, such as radiotherapy planning, surgical simulation, and for the derivation of volumetric based bio-markers.

Abdominal image non-rigid registration is a particularly challenging task due to the presence of multiple organs, many of which move independently or are influenced by the movement of adjacent structures (i.e. the diaphragm), contributing to independent deformations.

Among many existing registration methods, Thirion’s demons algorithm [11] is the most widely used for the computation of dense deformation between images [2] because of its linear complexity and simple implementation. This algorithm iteratively computes the best dense deformation field that minimizes the intensity dissimilarity between the images, and regularizes the deformation field to ensure spatial coherency by homogeneous isotropic smoothing with a Gaussian kernel.

However, the homogeneous smoothing step does not preserve possible discontinuities in the deformation field, which may be related to the independent movement of different organs. Thus, the resultant deformation field may be inaccurate. Several adaptive regularization approaches have been recently developed. They can be roughly classified into two categories: 1) Image-driven and 2) deformation field driven.

Image-driven adaptive regularization methods use a weighted regularization approach, where the regularization is inversely proportional to discontinuities derived from the image intensity domain. In [3], a tumor region is automatically segmented from the intensity image and used to control the smoothing operator. In [4], a stiffness parameter derived from the moving image intensities is used to control the smoothing process. In [5], a reliability-measure is used to control the smoothing amount with respect to the estimated image noise. In [6], the amount of smoothing is inversely proportional to the curvature of the image. In [7], a Hessian based structure detector is used to control the smoothing amount. In [8], a physical model generated from prior manual segmentation was used to control the smoothness amount and direction.

Deformation field driven methods use deformation field-based information to reduce the smoothing effect along the deformation field discontinuities. In [9], a specific filter is used to prevent over-smoothing along deformation-field discontinuities that are related to resections or retractions. However, this approach cannot be used to ensure coherent and independent deformation of different organs. In [10], a machine-learning approach is used to encode a task-specific deformation prior, that can be used later for the regularization. This approach requires accurate construction of the deformation prior for each registration task.

In this paper we present a local-affine adaptive smoothing approach for the regularization in the demons algorithm. Our approach models the dense deformation as a set of local affine transformations, and adaptively smooths the dense deformation field while preserving the discontinuities along the local affine components using the anisotropic smoothing approach [11]. We assume that voxels that are close, both spatially and in their intensity value, represent the same structure, and thus
Fig. 1. Synthetic example: (a)-(b) Axial slices from the reference (a) and moving (b) images; (c)-(d) Registration results of the demons algorithm (c) compared to our result (d), with the fixed image overlaid in red.

have similar affine motion. Thus, the local-affine modeling process assigns an affine transform to each voxel, by considering its local neighborhood voxels, weighted by their intensity similarity.

Fig. 1 illustrates the effect of our method compared to the original demons algorithm on a synthetic example. The coupling of efficient dense deformation estimation with local affine adaptive smoothing yields a better registration algorithm which is more suitable for the registration of abdominal images.

2. METHOD

Given a patient image \( I_p \), the goal is to find a dense deformation field \( D_p \) that minimizes its dissimilarity to the reference image \( I_r \). Thirion’s demons algorithm \[1\] computes the deformation field that minimizes the energy:

\[
\hat{D}_p = \arg\min_{D_p} E(I_p, I_r, D_p) + S(D_p)
\]  

(1)

where \( E(I_p, I_r, D_p) \) is the dissimilarity measure between the reference and deformed images, and \( S(D_p) \) is a regularization term that controls the smoothness of the resultant deformation field. The solution is found by applying the following two successive steps iteratively:

1. Compute an unconstrained dense deformation field that minimizes the dissimilarity between the patient and the reference images.

2. Regularize the deformation field by homogeneous isotropic Gaussian smoothing to ensure its spatial coherence.

Since the smoothing step may over-smooth the deformation field discontinuities that are related to independent movements of different organs, we replace the smoothing step (2) with a new anisotropic smoothing filter that is inversely proportional to the differences between the local affine transformations. Our smoothing step consists of the following components:

2.a) Fit an affine transformation \( A(\tilde{x}) \) to each voxel \( \tilde{x} \) based on its neighborhood \( \Omega_{\tilde{x}} \).

2.b) Compute the gradient of the affine transformations domain.

2.c) Apply adaptive smoothing \[11\] to the deformation field, based on the affine transformations gradient.

We will describe these components in detail next.

2.1. Local affine transformation fitting

The fitting of a local affine transformation to each voxel is defined as follows: For each voxel \( \tilde{x} \), find an affine transform \( A(\tilde{x}) \) that best approximates the deformation of the structure in this region with respect to the neighboring voxels \( \tilde{y} \in \Omega_{\tilde{x}} \) and the current estimation of their deformation vectors \( D_p(\tilde{y}) \). Since considering voxels in the neighborhood \( \Omega_{\tilde{x}} \) of \( \tilde{x} \) equally may introduce motions of different organs, we use a weighting function that prefers voxels with similar intensity values over voxels with large intensity differences. Consequently, the local affine fitting is formulated as a weighted least-squares problem:

\[
\hat{A}(\tilde{x}) = \arg\min_A \sum_{\tilde{y} \in \Omega_{\tilde{x}}} w_{\tilde{x}} \| A(\tilde{y}) - D_p(\tilde{y}) \|^2
\]  

(2)

The weights \( w_{\tilde{x}} \) are defined as:

\[
w_{\tilde{x}} = \exp \left( -\frac{(I(\tilde{x}) - I(\tilde{y}))^2}{2\sigma^2} \right)
\]  

(3)

where \( \sigma \) is a predefined scaling parameter, representing the expected signal intensity homogeneity within same structure. The solution can be found efficiently using Horn’s method \[12\], or using the SVD method \[13\].

2.2. Local affine domain gradient computation

We use the Frobenius metric between matrices:

\[
\| A_1 - A_2 \| = \sqrt{\sum_i \sum_j (A_1(i,j) - A_2(i,j))^2}
\]  

(4)
with appropriate scaling for the translational components of the affine transformation, to define the gradient of the local affine domain. The gradient is then computed using the finite differences approach.

### 2.3. Local affine adaptive smoothing

Given the local affine domain gradient $\nabla \hat{A}(\vec{x})$, we use the anisotropic diffusion operator to adaptively smooth the deformation vectors associated with each voxel, while preserving the discontinuities between local affine motions. Following the anisotropic diffusion approach presented in [11], our diffusion operator is defined as follows:

$$\frac{\partial D_p^r(\vec{x})}{\partial t} = \nabla c(\vec{x}) \cdot \nabla D_p^r + c(\vec{x}) \Delta D_p^r(\vec{X})$$

where $c(\vec{x})$ is the diffusion coefficient defined as:

$$c(\vec{x}) = \exp\left(-\frac{\| \nabla \hat{A}(\vec{x}) \|^2}{k^2}\right)$$

and $k$ is a predefined constant scaling parameter that differentiates between local affine differences that relate to independent organ movements and noise.

### Table 1. Registration results.

<table>
<thead>
<tr>
<th>Structure</th>
<th>Method</th>
<th>Dice (%)</th>
<th>Harmonic energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kidney 1</td>
<td>Our</td>
<td>0.8</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>Demons</td>
<td>0.8</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>Diff demons</td>
<td>0.59</td>
<td>4.53</td>
</tr>
<tr>
<td>Kidney 2</td>
<td>Our</td>
<td>0.87</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>Demons</td>
<td>0.87</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>Diff demons</td>
<td>0.86</td>
<td>2.73</td>
</tr>
<tr>
<td>Pelvis</td>
<td>Our</td>
<td>0.53</td>
<td>0.27</td>
</tr>
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</tr>
<tr>
<td></td>
<td>Diff demons</td>
<td>0.55</td>
<td>0.29</td>
</tr>
</tbody>
</table>

The first column is the structure that was registered. The second column is the method that was used for the registration. The third column is the Dice similarity measure between the manual segmentation of the structure and the deformed segmentation from the moving image. The fourth column is the harmonic energy of the resultant deformation field. For each dataset, the first row presents the results obtained using our method. The additional two rows present the results of the other algorithms.

### 3. RESULTS

#### 3.1. Synthetic example

We used our algorithm to register a 3D image with two crosses to a similar image, where each of the crosses has a translational movement of 1 voxel in each axis, in opposite directions. Fig. 1 presents the reference and moving images, and the registration results of the original demons algorithm [1] compared to our algorithm results. Our algorithm preserves the object boundaries much better compared to the demons result. The final Sum of Squared intensity Differences (SSD) between the fixed and the registered image using our method was 7.3, while the demons algorithm result yielded a SSD of 43.04.

#### 3.2. Abdominal CT registration

To evaluate our method on real images, we randomly collected three CT scans of patients with various pathologies from the hospital archive, and applied inter-patient registration. Initially, all the images were globally aligned using affine registration with the elastix toolbox [14]. Next, the kidney and pelvis regions were extracted from the entire abdominal scan. The properties of the images that were used for the non-rigid registration experiment were as follows: The kidney image size was 96x96x150 voxels, and the pelvis image size was 234x162x128. Both had physical spacing of 1.17x1.17x1.2mm.

Finally, we applied non-rigid registration to the pelvis and the two kidneys using our method, and compared its results to
that of the original demon’s registration \[1\] and to the diffeo-
orphic demons algorithm \[13\]. To accelerate the registration process, we used our anisotropic smoothing approach only as a post-processing step on the demons registration result. The parameters that were used for our anisotropic smoothing were as follows: \( \sigma = 15, k = 1 \), the neighborhood radius used for affine tranformation fitting was 1 and the number of smoothing iterations was 30. Fig. 2 presents a kidney registration example.

To quantitatively measure our method’s performance, the kidney and the pelvis were segmented manually on both images, and aligned using the resultant deformation fields. The Dice similarity measure was used to evaluate the accuracy of the registration, and the Harmonic energy measure \[15\], which is inversely proportional to the deformation field smoothness, was used to quantify the smoothness of the resultant deformation field. Table 1 presents the results for both the two kidneys and the pelvis experiments. For all experiments, our method yielded a smoother deformation field, while preserving the registration accuracy. This is in contrast to the existing regularization methods that suffer from a compromise between the accuracy of the resulting deformation field and its smoothness \[16\].

4. CONCLUSIONS

We have presented a local-affine adaptive smoothing approach for the regularization of dense deformation field during demons registration. Our approach locally fits the affine transformation that best represents the local motion of different objects. Then, it smooths the original deformation field while preserving its local affine discontinuities. Representative results on both a synthetic example and clinical abdominal CT images demonstrate that our method produces smoother deformation-fields while preserving their accuracy. In the future we plan to use this method for multiple organ atlas-based abdominal image segmentation.

5. REFERENCES


