Multimodal image registration by edge attraction and regularization using a B-spline grid

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ABSTRACT

Multi modal image registration enables images from different modalities to be analyzed in the same coordinate system. The class of B-spline-based methods that maximize the Mutual Information between images produce satisfactory result in general, but are often complex and can converge slowly. The popular Demons algorithm, while being fast and easy to implement, produces unrealistic deformation fields and is sensitive to illumination differences between the two images, which makes it unsuitable for multi-modal registration in its original form.

We propose a registration algorithm that combines a B-spline grid with deformations driven by image forces. The algorithm is easy to implement and is robust against large differences in the appearance between the images to register. The deformation is driven by attraction-forces between the edges in both images, and a B-spline grid is used to regularize the sparse deformation field. The grid is updated using an original approach by weighting the deformation forces for each pixel individually with the edge strengths. This approach makes the algorithm perform well even if not all corresponding edges are present.

We report preliminary results by applying the proposed algorithm to a set of (multi-modal) test images. The results show that the proposed method performs well, but is less accurate than state of the art registration methods based on Mutual Information. In addition, the algorithm is used to register test images to manually drawn line images in order to demonstrate the algorithm's robustness.

Keywords: Multi-modal registration, B-spline grid, edge attraction, sparse deformation forces

1. PURPOSE

Image registration is an important tool for a wide range of applications in medical diagnosis, for example in the detection of tumors[15] and for the analysis of motions in gated data.[2] When applied to different modalities, it enables the different images to be analyzed in the same coordinate system. Since different modalities present different aspects of the physiology of the patient, combining the different modalities can simplify diagnostics and make it more reliable. However, the difference in appearance between the images poses an extra challenge for a registration algorithm.

The current range of common region based image registration algorithms can be divided in two classes. Both classes usually adopt a multiscale approach in order to prevent finding a local minimum, and to speed up the registration process.

The first class employs a B-spline grid to describe the deformation field, which is optimized by minimizing/maximizing a similarity measure. Using Mutual Information (MI) as a similarity measure, these methods have been reported successfully for multi-modal registration.[10, 12, 15] While the use of a B-spline grid can cause problems when describing rotational deformations,[5] it has the advantage that the deformations are described in an efficient way and are physically realistic.[11] Additionally, the deformations can be regularized in various ways, for example by minimizing bending energies or penalizing small Jacobians.[12]

The second class uses image forces calculated at the pixels/voxels to drive the registration process. The most notable method is the popular Demons algorithm,[13] which is related to optical flow. The deformation is obtained for each pixel individually by calculating image forces, and regularization of the deformation field is performed by Gaussian diffusion. Its popularity can probably be attributed to its simple implementation and its fast convergence. The Demons algorithm is capable of handling extreme deformations, which can also be
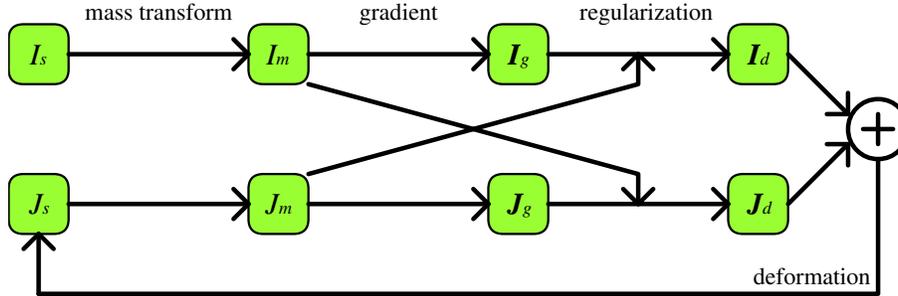
Figure 1: Schematic representation of the proposed registration algorithm. The iterations are repeated, while the scale s is reduced.

a downside, since such deformations are usually not physically realistic. Another problem with the Demons algorithm is that it assumes pixel intensities in corresponding regions between images to be similar, which causes problems in images containing much noise or artifacts such as bias fields.[11] Moreover, this makes the Demons algorithm unsuitable for multi-modal registration in its original form.

We propose a registration algorithm that is a combination of both classes. The algorithm is relatively easy to implement, has fast convergence, and is robust against large differences in the appearance between the images to register.

2. METHOD

Given two input images images I and J, which can be 2D images ($\mathbb{R}^2 \rightarrow \mathbb{R}$) or volumetric data ($\mathbb{R}^3 \rightarrow \mathbb{R}$), the registration problem is defined as deforming image J such that the elements in J match with the elements in I. We adopt a scale space approach, in which the scale s is defined as the amount of diffusion: $I_s = I \otimes g_s$, where g_s is the kernel for scale s as proposed by Lindeberg.[9]

2.1 Concept

The proposed algorithm is based on the concept of attraction: edges in one image are attracted to the edges in the other image; even though (the distribution of) intensities of two images from different modalities can be rather different, their edges are usually approximately at the same position[1] (PET-CT being one exception). To regularize the sparse attraction-forces calculated from the image data, the deformation is described using a B-spline grid. Edge attraction registration algorithms usually suffer from the fact that some edges may not be present in both modalities, and from the fact that the deformation is ill defined at the regions in between the edges.[5] The use of a B-spline grid enables us to solve these problems by weighting the forces with the edge strengths for each pixel individually.

2.2 Scale space approach

The registration is achieved in an iterative manner: at each iteration two mass images are calculated, whose gradients determine the deformation (figure 1). This process is repeated while the scale s is reduced until it reaches a predefined value. In this way, the algorithm starts with registering the coarse edges of the images, and more detailed edges are introduced as the scale is reduced during the registration process.

In most publications on image registration, the scale is reduced with factors of two, and there is a fixed number of iterations at each scale. In contrast, we consider the scale as a continuous dimension which is sampled. Therefore, we chose to smoothly decrease the scale and define a fixed number of iterations p_{SS} for each factor-of-two reduction. This has the effect that the amount of deformation found at each iteration scales smoothly with scale, which will increase the chance of finding the global optimum registration. The parameter p_{SS} represents the scale sampling, and is comparable to the "number of iterations per scale" parameter of other registration algorithms.
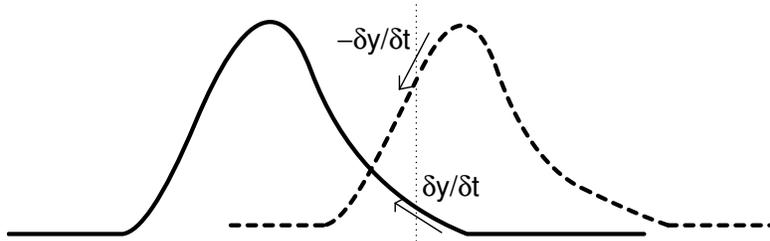
Figure 2: Illustration of how the attraction-forces are calculated from the mass images. Due to the scale-space approach, the coarse edges are first aligned. Smaller edges are aligned as the scale is reduced.

2.3 Calculating the mass image

The main concept of the proposed algorithm is that *objects* attract each-other, where an object is a group of pixels/voxels with high intensities. These objects are assumed to be sparsely distributed over the image. Since few images have their pixels intensities distributed in this manner, the first step of the algorithm is to obtain the mass-images I_m and J_m from I_s and J_s. Because images can be considered similar if their intensity changes occur at the same location, we propose to use the gradient magnitude to detect intensity changes in both images[*]:

$$
\begin{aligned}
I_{m,a} &= |\nabla I_s|, & (1)\\
J_{m,a} &= |\nabla J_s|. & (2)
\end{aligned}
$$

Further, a series of operations is applied to normalize the mass image. (To calculate J_m, the same steps are applied as for I_m.) First, small masses caused by noise or small structures are removed using the mean of the mass image as a reference:

$$
I_{m,b} = \begin{cases} I_{m,a} - \frac{\mu(I_{m,a})}{2} & \text{if } I_{m,a}(\mathbf{x}) > \frac{\mu(I_{m,a})}{2} \\ 0 & \text{otherwise} \end{cases}, \tag{3}
$$

with $\mu(\cdot)$ the mean operator. Next, diffusion is applied to the mass image to smooth the mass image and increase the region of attraction:

$$
I_{m,c} = I_{m,b} \otimes g_s. \tag{4}
$$

Finally, in order to obtain values that are neither too low (and not cause any movement), or too high (causing overshoot), the mass images are normalized:

$$
I_m = \frac{2I_{m,c}}{\mu(I_{m,c}) + \sigma(I_{m,c})}, \tag{5}
$$

with $\sigma(\cdot)$ the standard deviation operator. The values of the mass image will be lowered if either the mean or the standard deviation is high. In the presence of relatively high noise, the mass image will contain many small masses in the background, particularly for lower scale values. Since in such a case the mean and standard deviation are both high, the values of I_m and J_m will be reduced, thereby preventing movement caused by false masses.

2.4 Calculating and regularizing the deformation

Similar to a proposed improvement on the Demons algorithm,[14] the total deformation is calculated by combining the found deformations of the moving image as well as the static image. First, an initial "gravity field" is obtained by calculating the gradient of the mass (see figure 2):

---

[*]Depending on the content of the images to register, other transformations (such as the Laplacian operator) may work well too.

$$\mathbf{I}_g = \nabla I_m \cdot s \cdot p_{\text{speed}} \tag{6}$$

$$\mathbf{J}_g = -\nabla J_m \cdot s \cdot p_{\text{speed}} \tag{7}$$

where p_{speed} is a parameter of the proposed algorithm that can be used to influence the relative strength of the deformation at each iteration (its default value, which works well in most cases, is 1).

Similar to the Demons algorithm, the vector fields $\mathbf{I}_g$ and $\mathbf{J}_g$ describe the deformation for each pixel. However, since in our situation the intensities are sparsely distributed over the image, applying diffusion to $\mathbf{I}_g$ and $\mathbf{J}_g$ (as is done in the Demons algorithm) will lead to unsatisfactory results. Our problem is analog to the point matching problem, in which a sparse set of points describes a deformation of the whole image. For this problem, a solution based on B-spline grids has been proposed by Lee et. al.[3,7] In order to apply this method to our problem, we modify Equation (5) in Lee et. al., which describes how the values of the knots of the B-spline grid are updated using a set of corresponding points. We introduce a weight per pixel α (in this context each pixel $\mathbf{x}$ is a point):

$$\phi'_{i,j} = \frac{\sum_{\forall \mathbf{x}} \alpha \omega_{\mathbf{x}}^2 \phi_{\mathbf{x}}}{\sum_{\forall \mathbf{x}} \alpha \omega_{\mathbf{x}}^2}, \tag{8}$$

where ϕ_c is the deformation to apply at a certain point, weighted by the B-spline basis functions, ω_c is a normalization factor calculated from the B-spline coefficients. The weight factor α that we introduced is $\alpha = J_m(\mathbf{x})$ when we regularize $\mathbf{I}_g$ and $\alpha = I_m(\mathbf{x})$ when we regularize $\mathbf{J}_g$. The underlying idea to this approach is that the deformation is calculated by evaluating the gravity field created by one image at the location of the mass in the other image. In addition to enabling the deformation to be described by a sparse set of pixels, the introduced weight factor also has a noise regulating effect when used in combination with the normalization step in the calculation of the mass images.

To prevent the grid from folding, the deformation ϕ_c should be limited to 0.48 times the grid sampling.[8] In order to apply this limit in a smooth fashion, without simply truncating the data, we apply the following formula:

$$\phi_{c,limited} = 0.48 \cdot (e^{-|\phi_c|/0.48} - 1) \cdot sign(\phi_c). \tag{9}$$

This function has a slope of 1 at the origin and has an asymptote at $+0.48$ and -0.48.

By introducing the parameter p_{grid} to set the grid sampling at the final scale ($s = 1$), the sampling of the B-spline grid is chosen relative to the scale. After the B-spline grid has been constructed, the deformation that it describes is evaluated every pixel location to obtain the deformation fields $\mathbf{I}_d$ and $\mathbf{J}_d$. These are combined and used to update the deformation field used to transform J_s (figure 1).

3. EXPERIMENTS

3.1 Materials

In order to investigate the performance of the proposed method, preliminary experiments were performed on two-dimensional slices extracted from simulated MRI images ($181 \times 217 \times 181$ voxels, spaced 1 mm in all dimensions, with a slice thickness of 1 mm). These images were obtained from the Brainweb database[6][†]. We obtained T1 and T2 weighted images with increasing levels of noise, and an intensity non-uniformity of 40%. The algorithm was applied to register T1 images to T2 images, where the T2 images were deformed with a random but known deformations. A series of 14 slices were selected as a training set to tune the algorithm parameters. Another series of 28 slices (not overlapping with the training set) was selected to function as a test set. For practical reasons, the slices were padded to 256×256 pixels. The proposed algorithm was compared with a registration algorithm that optimizes Mutual Information (MI). We used the implementation that is freely available in the Elastix toolkit[4][‡].
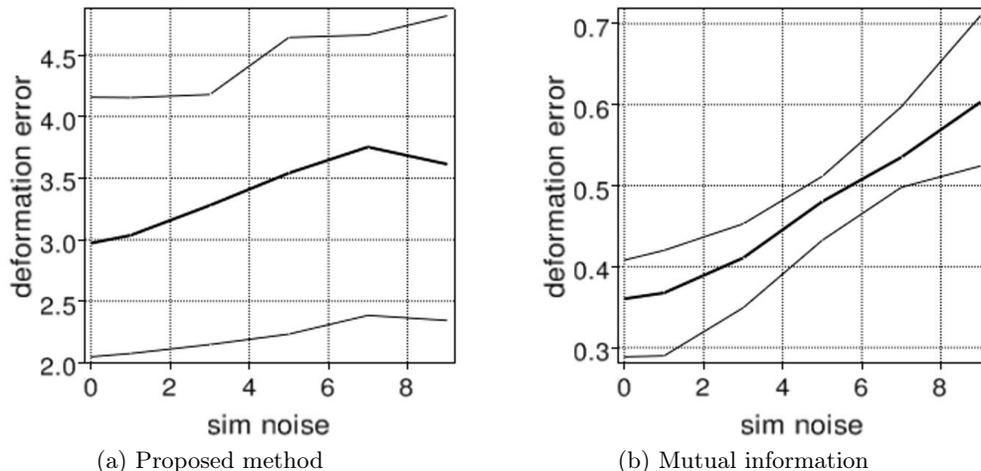
Parameter	Value		Parameter	Value
scale sampling p_{ss}	50		'MaximumNumberOfIterations'	250
final grid sampling p_{grid}	30		'FinalGridSpacingInPhysicalUnits'	20
(a) Proposed algorithm			(b) Mutual information	

Table 1: The found optimal parameter values that were optimized using the test set.

(a) Proposed method   (b) Mutual information

Figure 3: Illustration of the mean deformartion error for different noise levels. Depicted are the median, 25 percentile and 75 percentile for the different slices in the test set.

3.2 Random deformations

The deformations were calculated by filling two images with randomly generated Gaussian blobs. These two images were then used to describe the deformation for x and y, respectively. The position, sign, standard deviation and amplitude of the Gaussian blobs were all randomly varied. By setting the seed for the random number generator before each experiment, the deformations could be repeated, such that the deformation for a particular slice is always the same.

3.3 Results

The results of the parameter tuning is illustrated in table 1. For both algorithms, we tuned the two parameters that have the greatest effect on the end result. The parameters p_{ss} and p_{grid} are analog to the parameters 'MaximumNumberOfIterations' and 'FinalGridSpacingInPhysicalUnits', respectively. For the MI-based registration, we further used the parameters values as suggested in the paper[4] (see Appendix A).

The algorithm was applied to find the deformation between the images, which was then compared with the known deformation. In the comparison, pixels belonging to the background were not taken into account. The mean deformation error for the different noise levels is shown in figure 3.

To give an impression of the deformations applied in these experiments, and to enable visual assessment of the results, we show two examples in figure 4.

To illustrate the robustness of the proposed method against variations in image intensities between the two images, we registered a T2 weighted image to a manually drawn line image (figure 5). To obtain the mass image J_m for the line image, equation 2 is replaced simply by $J_m = J_s$, because its lines correspond to the edges in the T1 image.

4. DISCUSSION

From the results in figure 4 it can be seen that the proposed algorithm is capable of producing visually pleasing results when registering T1 images to T2 images. The results of the quantitative experiments (figure 3) indicate
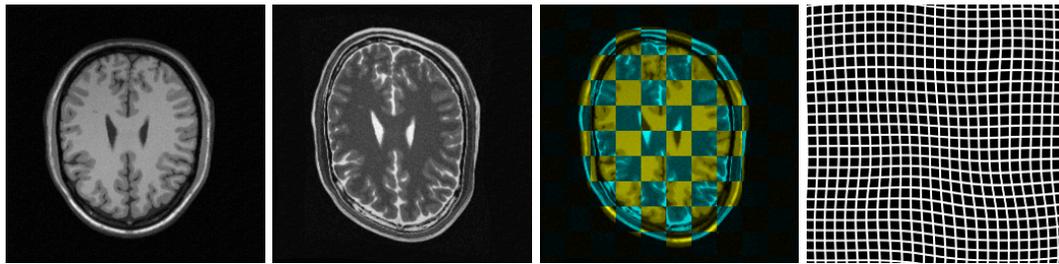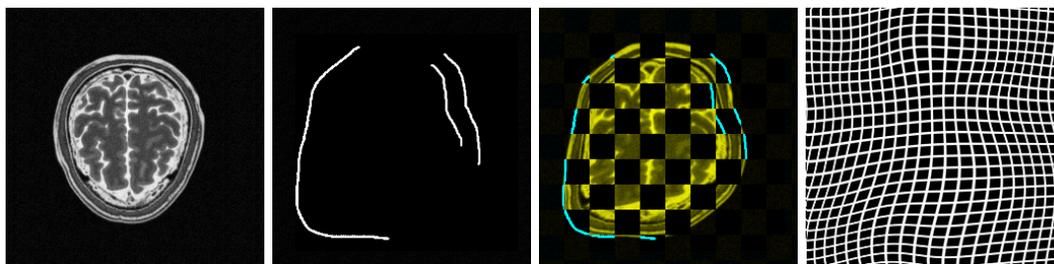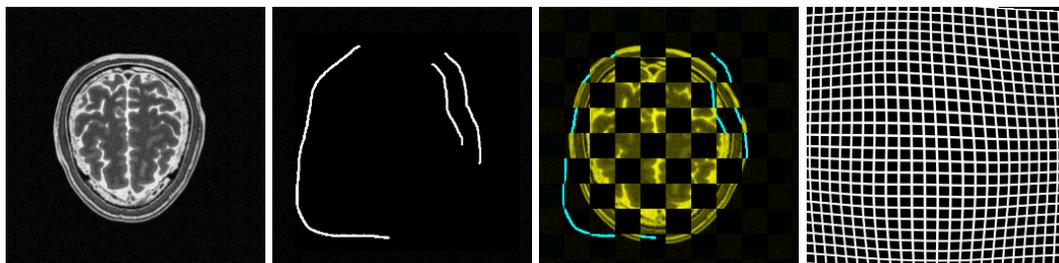
(a)
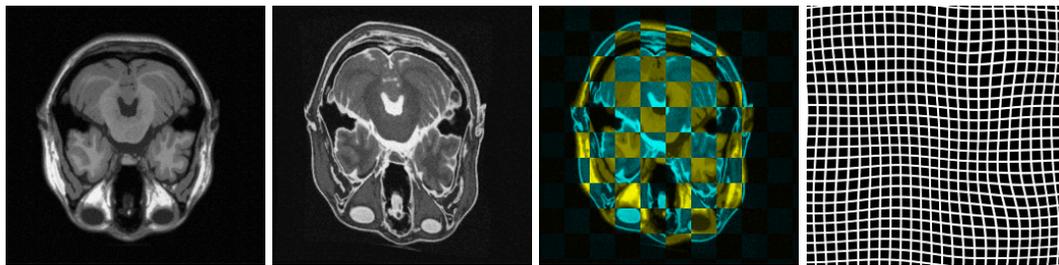
(b)

Figure 4: Illustration of two example results for registering a T1 image with a T2 image. From left to right: the T1 image, the T2 image, the result, the found deformation field.

(a) Proposed algorithm

(b) MI-based

Figure 5: Illustration of the results (of the proposed method and the MI-based method) of registering a T2 image with a manually drawn line image.

that the mean deformation error is a factor 3 larger than the pixel size, which is acceptable for some applications. However, it can also be seen that the MI-based registration performs much better. One explanation is that the proposed algorithm allows more extreme (unnatural) deformations, since only the extra deformation at each iteration is regularized, and not the total deformation. Another explanation is that—due to the normalization—the large deformation forces near the skull prevent the smaller forces in the brain from applying enough deformation.To what extend both causes contribute to the relatively bad accuracy of the proposed algorithm remains to be investigated.

The result in figure 5 illustrates the performance of the proposed algorithm when the amount of corresponding content between the images is low. This registration problem is particularly hard for many registration algorithms. The good performance of the proposed algorithm can be explained by the combination of using a B-spline grid and weighting the deformations of the individual pixels with the edge strength. This example suggests that, for some registration problems, the proposed algorithm can perform good compared to other algorithms.

The proposed method will have to be quantitatively evaluated on real-world data, for example on inter-patient registration problems. We expect that the proposed algorithm's ability to deal with large differences in the appearance of images is a great advantage for such registration problems. Additionally, the algorithm should be evaluated on other (single modal) registration problems.

Like the original Demons algorithm, the proposed algorithm has a step size parameter (p_{speed}), which could be optimized during each iteration using a line search method.[5] This will likely increase the stability of the method and may further improve convergence.

Further we note that the current implementation uses a single thread, but many parts of the method (e.g. diffusion, calculating the B-spline grid) can be easily parallelized to increase the speed of the algorithm.

The transformation to obtain the mass images is performed using a simple gradient magnitude transform. More complex transforms that extract specific image features that are present in both images may improve the results. Such a transform may be chosen depending on the type of images to register. Additionally, the normalization of the mass images may currently not be optimal. More research to these aspects of the presented algorithm is required.

5. CONCLUSIONS

We propose a new registration method that uses image forces to drive the registration process. Our main contribution is the combination of a B-spline grid with image-driven deformation forces in a scale space setting, and the approach to regularize the sparse forces to obtain a realistic deformation. The proposed method is fast and relatively easy to implement. Preliminary experiments on simulated MRI data show that the proposed method performs well, but is less accurate than state of the art registration methods based on Mutual Information.

Appendix A: Elastix parameters

Parameters used for the `Elastix` application:

```
           MaximumNumberOfIterations:  250
    FinalGridSpacingInPhysicalUnits:  20
                       Registration:  "MultiResolutionRegistration"
                          Optimizer:  "AdaptiveStochasticGradientDescent"
                          Transform:  "BSplineTransform"
                   FixedImagePyramid:  "FixedRecursiveImagePyramid"
                  MovingImagePyramid:  "MovingRecursiveImagePyramid"
                NumberOfResolutions:  4
                             Metric:  "AdvancedMattesMutualInformation"
              NumberOfHistogramBins:  32
              NumberOfSpatialSamples:  2048
             NewSamplesEveryIteration:  True
```

```
              ImageSampler:  "RandomCoordinate"
              Interpolator:  "BSplineInterpolator"
      BSplineInterpolationOrder:  1
 FinalBSplineInterpolationOrder:  3
                Resampler:  "DefaultResampler"
      ResampleInterpolator:  "FinalBSplineInterpolator"
          DefaultPixelValue:  0
   FixedInternalImagePixelType:  "float"
         UseDirectionCosines:  True
 MovingInternalImagePixelType:  "float"
     HowToCombineTransforms:  "Compose"
```

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