Published in final edited form as:

Inf Process Med Imaging. 2009 ; 21: 447–458.

A Non-rigid Registration Framework That Accommodates Resection and Retraction

Petter Risholm^{1,2}, Eigil Samset¹, Ion-Florin Talos², and William Wells²

Petter Risholm: pettri@bwh.harvard.edu

¹ Center of Mathematics for Applications, University of Oslo

² Harvard Medical School, Brigham and Womens Hospital

Abstract

Traditional non-rigid registration algorithms are incapable of accurately registering intra-operative with pre-operative images whenever tissue has been resected or retracted. In this work we present methods for detecting and handling retraction and resection. The registration framework is based on the bijective Demons algorithm using an anisotropic diffusion smoother. Retraction is detected at areas of the deformation field with high internal strain and the estimated retraction boundary is integrated as a diffusion boundary in the smoother to allow discontinuities to develop across the resection boundary. Resection is detected by a level set method evolving in the space where image intensities disagree. The estimated resection is integrated into the smoother as a diffusion sink to restrict image forces originating inside the resection from being diffused to surrounding areas. In addition, the deformation field is continuous across the diffusion sink boundary which allow us to move the boundary of the diffusion sink without changing values in the deformation field (no interpolation or extrapolation is needed). We present preliminary results on both synthetic and clinical data which clearly shows the added value of explicitly modeling these processes in a registration framework.

1 Introduction

The most common approach to image guided neurosurgery is the integration of pre-operative anatomical and functional images, as well as planned retraction and resection boundaries, with a neurosurgical navigation system which guides the surgeon during surgery. However, considerable brain-shifts due to various factors such as gravity, edema, tumor mass effect and cerebrospinal fluid leakage have been reported after the craniotomy and opening of the dura [1]. This decreases the intra-operative accuracy of these navigation systems significantly. Secondly, as a result of resection and retraction, additional morphological changes occur which render the pre-operative images obsolete with respect to the real intra-operative anatomy. The introduction of intra-operative MR scanners has provided the surgeon with anatomically correct images intra-operatively which facilitates a more aggressive resection. Unfortunately, intra-operative MR scanners are not typically capable of providing accurate functional information during a procedure. Hence, mapping the pre-operative image data to reflect intra-operative anatomy will increase the accuracy of the neurosurgical navigation system and hopefully improve the outcome of the neurosurgical procedure. Numerous nonrigid registration algorithms have been proposed to handle brain shifts. However, there are only a limited number of methods proposed to handle retraction and resection. Retraction and resection pose two different challenges – retraction requires the algorithm to facilitate development of discontinuities in the deformation field along the retraction boundary while resection necessitates the algorithm to handle data which is present in the pre-operative image but missing in the intra-operative image.

In [2] Periaswamy et al proposed a registration framework which handles missing data by applying the expectation maximization method to iteratively estimate the missing data and the registration parameters. However, their missing data model does not constrain the localization of the missing data in any way. For modeling of resection one can assume that data is not sporadically missing throughout the image, but confined to a single area. Miga et al proposed in [3] to use a bio-mechanical model to handle resection and retraction. They applied no automatic means of detecting the missing data due to resection or the retracted areas; they manually delineated the resected area and used a calibrated microscope to determine the position of the retractor during surgery. Bio-mechanical models are frequently simulated with finite element methods (FEM) which require a tessellation of the image domain. FEM based methods with automatic detection of retraction and resection require retessellation during the registration procedure which is a non-trivial and time consuming process and thus may not be very practical for intra-operative registration.

The demons algorithm[4] has over the last decade proven to be a fast, accurate and robust monomodal non-rigid registration algorithm[5]. It can be viewed as a two-stage energy minimization technique[6]. First it finds an unconstrained dense deformation field which matches the images whereupon it regularizes the deformation field to an elastic or fluid deformation by smoothing it with a Gaussian low-pass filter. In his original paper, Thirion pointed out that Gaussian smoothing can be interpreted as a diffusion process. In [7] Perona and Malik proposed a smoothing filter modeled by a non-linear anisotropic diffusion process where diffusion can be restricted across boundaries. We will show how the flexibility of this diffusion based smoother can be exploited to handle resection and retraction. In particular, we will model resection by what we have termed a *diffusion sink* and retraction with a *diffusion boundary*. Some of the ideas we have applied in our work are influenced by developments in the vision literature on handling occlusions and discontinuities in the estimation of optical flow [8].

2 Methods

2.1 Registration

Demons Registration—We wish to register two monomodal images, a pre-operative image $P(x)$, $x \in \Omega_P$ with an intra-operative image $I(x)$, $x \in \Omega_I$ where Ω_P and Ω_I are the pre-operative and intra-operative image domains respectively. By posing the registration as a diffusion process, the demons algorithm[4] is effective at finding the deformation $U_{IP}(x) = x + u_{IP}(x)$, where u_{IP} is a displacement field, which puts P into agreement with I . It is a two-step iterative method where the first step consist of finding an unconstrained velocity field with an optical flow computation followed by a smoothing step to regularize the deformation. The velocity field is computed by

$$v_{IP}^n(x) = \frac{(P \circ U_{IP}^{n-1}(x) - I(x)) \nabla I(x)}{(P \circ U_{IP}^{n-1}(x) - I(x))^2 + |\nabla I(x)|^2}, \quad (1)$$

where $\circ$ denotes composition. The regularization step, consisting of the application of a smoothing filter S can either be applied to the updated deformation field to achieve an elastic deformation $U_{IP}^n(x) = S(v_{IP}^n(x) + U_{IP}^{n-1}(x))$, or directly to the update which will result in a fluid deformation:

$$\mathbf{U}_{IP}^n(\mathbf{x}) = \mathbf{U}_{IP}^{n-1}(\mathbf{x}) + S(\mathbf{u}_{IP}^n(\mathbf{x})). \quad (2)$$

In the traditional Demons algorithm, the smoother S is typically a Gaussian low-pass filter. This two-stage process proceeds until a convergence criterion is reached. The fluid version of the demons algorithm was applied for this work because of its ability to handle large deformations. In the following, whenever it is clear from the context, we will drop the dependence on $\mathbf{x}$.

Bijjective Demons—Because of the asymmetry in Eq. (1), there is no guarantee the final deformation field will be bijective. That is, if we compute $\mathbf{U}_{IP}$ and $\mathbf{U}_{PI}$ then there is no guarantee that $\mathbf{U}_{IP} \circ \mathbf{U}_{PI} = Id_{\Omega_I}$ or $\mathbf{U}_{PI} \circ \mathbf{U}_{IP} = Id_{\Omega_P}$ where Id_{Ω_i} denotes the identity over the domain Ω_i . A general way of enforcing bijectivity of a deformation field is to put the constraint $|J| > 0$ on the Jacobian matrix of the deformation field. However, it is computationally intensive to enforce this constraint[9]. Thirion[4] suggested a simpler solution where $\mathbf{U}_{IP}^*$, $\mathbf{U}_{PI}^*$ and the residual $\mathbf{r}_{PI} = \mathbf{u}_{PI}^* + \mathbf{u}_{IP}^* \circ \mathbf{U}_{PI}^*$ are all calculated at each iteration. By subtracting half the residual

from both deformation fields one can constrain them to be bijective: $\mathbf{U}_{PI}^n = \mathbf{U}_{PI}^{n,*} - \frac{1}{2}\mathbf{r}_{PI}^n$ and

$$\mathbf{U}_{IP}^n = \mathbf{U}_{IP}^{n,*} - \frac{1}{2}\mathbf{r}_{PI}^n \circ \mathbf{U}_{IP}^{n,*}.$$

Not only does this enforce bijectivity, it also provides us with the inverse deformation fields $\mathbf{U}_{PI} = \mathbf{U}_{IP}^{-1}$ and $\mathbf{U}_{IP} = \mathbf{U}_{PI}^{-1}$ for little extra computational cost. We will model retraction by allowing discontinuities to develop at certain areas of the deformation fields in such a way that $\mathbf{r}_{PI}$ will be close to zero while $\mathbf{r}_{IP}$ will have large residuals around the area of the discontinuity (see Fig. 1). Hence, we can guarantee that $\mathbf{U}_{IP} \circ \mathbf{U}_{PI} = Id_{\Omega_P}$, but conversely we will have $\mathbf{U}_{PI} \circ \mathbf{U}_{IP} \neq Id_{\Omega_I}$ around this area.

Directional Diffusion as a Smoothing Process—Mathematically the diffusion process can be formulated as $\frac{\partial}{\partial t} \mathbf{q}(\mathbf{x}, t) = \nabla \cdot (C(\mathbf{x}) \nabla \mathbf{q}(\mathbf{x}, t))$, where C controls the diffusion strength. Let us discretize this equation in 1D:

$$\frac{\partial}{\partial t} \mathbf{q}(x, t) = \nabla \cdot [C(x) \nabla \mathbf{q}(x, t)] \quad (3)$$

$$= \frac{1}{\Delta x^2} \left[C \left(x + \frac{\Delta x}{2} \right) (\mathbf{q}(x + \Delta x, t) - \mathbf{q}(x, t)) - C \left(x - \frac{\Delta x}{2} \right) (\mathbf{q}(x, t) - \mathbf{q}(x - \Delta x, t)) \right]. \quad (4)$$

At each point we calculate directional differences (East and West). We generalize the traditional diffusion model in Eq. (4) by introducing a separate conductance function for each direction:

$$\frac{1}{\Delta x^2} (C_E(x + \frac{\Delta x}{2})(\mathbf{q}(x + \Delta x, t) - \mathbf{q}(x, t)) - C_W(x - \frac{\Delta x}{2})(\mathbf{q}(x, t) - \mathbf{q}(x - \Delta x, t))). \quad (5)$$

To ease readability we rewrite Eq. (5) as $\frac{1}{\Delta x^2}(\Lambda_E(x, t) - \Lambda_W(x, t))$. By using upwind differencing on the left hand side the update equation becomes $q(x, t + 1) = q(x, t) + \mu(\Lambda_E(x, t) - \Lambda_W(x, t))$,

where $\mu = \frac{\Delta t}{\Delta x^2}$. It becomes evident from Eq. (5) that a directional difference eastwards is analogous to diffusion in the opposite direction. We will operate with a separate conductance map for each diffusion direction. For the 2D case we will have C_E , C_W , C_N and C_S (due to space constraints we will refer to them collectively as $C_{E|W|N|S}$) which provides flexibility in restricting diffusion. One can for instance allow diffusion in one direction while restricting diffusion in the opposite direction which will prove useful for modeling a diffusion sink. The conductance term can be modeled in different ways[7]. We model the conductance in a certain direction at point x through the relation $C_{E|W|N|S}(x) = 1 - B_{E|W|N|S}(x)$, where $B_{E|W|N|S}$ are binary directional boundary maps specifying whether a diffusion boundary should occur at position x . Update Eq. (2) can thereby be rewritten as

$$U_{IP}^n = U_{IP}^{n-1} + S(U_{IP}^n; \mu, \eta, B_{E|W|N|S}), \quad (6)$$

where η defines the number of diffusion iterations.

Diffusion Boundary—To accommodate for the development of discontinuities along a retraction path, the tear due to retraction will be modeled as a diffusion boundary. Let us define a label map

$$\Phi(p) = \begin{cases} 1, & \text{if } p \text{ is located on the tear.} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

for p on the lattice $(1+m\frac{\Delta x}{2}, 1+n\frac{\Delta y}{2})$, $m = 1 \dots M-1$, $n = 1 \dots N-1$ in Ω_P . To restrict diffusion across the tear and thereby allow a discontinuity to develop, values in Φ are incorporated into the directional boundary maps as follows:

$$B_{EW} \left(x + \frac{\Delta x}{2}, y \right) = \begin{cases} 1, & \text{if } \Phi(x + \frac{\Delta x}{2}, y - \frac{\Delta y}{2}) + \Phi(x + \frac{\Delta x}{2}, y + \frac{\Delta y}{2}) = 2 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

$$B_{NS} \left(x, y + \frac{\Delta y}{2} \right) = \begin{cases} 1, & \text{if } \Phi(x + \frac{\Delta x}{2}, y + \frac{\Delta y}{2}) + \Phi(x - \frac{\Delta x}{2}, y + \frac{\Delta y}{2}) = 2 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Diffusion Sink—Another diffusion restriction which will prove useful for modeling resection is what we have termed a diffusion sink. A diffusion sink is basically an area $\Omega_{R_I} \in \Omega_I$ (resected area) where diffusion is allowed into the area and not out of it. This diffusion sink provides us with a number of nice properties 1) the deformation field will be continuous across the boundary of Ω_{R_I} denoted by $\partial\Omega_{R_I}$, 2) even though a pixel is initially labeled as resected it might change label to non-resected later in the registration procedure. Because the deformation field is continuous across $\partial\Omega_{R_I}$ we can move the boundary of the diffusion sink without changing values in the deformation field (no interpolation from the deformations on $\partial\Omega_{R_I}$ to the areas

which changed label from resected to non-resected) and 3) unwanted demon forces occurring within Ω_{R_I} will not affect areas outside. Let us define a label map, Ψ , on the lattice ($m\Delta x$, $n\Delta y$), $m = 1 \dots M$, $n = 1 \dots N$ which takes on values 1 at locations assumed to be resected and 0 at locations outside the resection. A diffusion sink can then be incorporated in the anisotropic diffusion by using the following directional boundaries for the x -direction:

$$B_E \left(x + \frac{\Delta x}{2}, y \right) = |\Psi(x, y) - \Psi(x + \Delta x, y)|(1 - \Psi(x, y)) \quad (10)$$

$$B_W \left(x - \frac{\Delta x}{2}, y \right) = |\Psi(x, y) - \Psi(x - \Delta x, y)|(1 - \Psi(x, y)), \quad (11)$$

and the boundaries, B_N and B_S , for the y -direction are derived similarly. Figure 2 provides examples of applying diffusion boundaries and a diffusion sink to a smoothing problem.

2.2 Modeling Retraction

Tearing of tissue has been modeled in surgical simulators where tissue tears whenever the strain/stress of the deformation applied to the tissue exceeds a certain threshold[10]. We apply a similar model – around the area of retraction, where there are discontinuities in the movement of tissue, our assumption is that a considerable strain will build up in the deformation field as the registration algorithm proceeds to match the images (see Fig. 1). The general idea is to let the registration proceed until a location in Ω_P is found where the strain exceeds a certain threshold. From this location the tear is propagated along the direction normal to the direction of maximal strain until the strain drops below the threshold. The algorithm proceeds by iterating between registering the images and estimating the tear.

Detecting Tearing of Deformation Field—For in-plane problems the strain tensor can be expressed as

$$\boldsymbol{\varepsilon}(\mathbf{x}) = \begin{bmatrix} \varepsilon_{xx} & \varepsilon_{xy} \\ \varepsilon_{xy} & \varepsilon_{yy} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathbf{u}_x}{\partial x} & \frac{\partial \mathbf{u}_x}{\partial y} + \frac{\partial \mathbf{u}_y}{\partial x} \\ \frac{\partial \mathbf{u}_x}{\partial y} + \frac{\partial \mathbf{u}_y}{\partial x} & \frac{\partial \mathbf{u}_y}{\partial y} \end{bmatrix}. \quad (12)$$

At an area of retraction in Ω_P , deformation vectors on different sides of the retraction in U_{PI} will point towards each other. Hence, the minimum eigenvalue and the corresponding eigenvector, $\lambda(\mathbf{x})$ and $\mathbf{v}(\mathbf{x})$, of the strain tensor in Ω_P determines the direction and magnitude of maximum strain. At each iteration of the registration procedure we compute the minimum eigenvalue $\lambda(\mathbf{p})$ and the corresponding eigenvector $\mathbf{v}(\mathbf{p})$ of the strain at interpixel locations

$(1 + m\frac{\Delta x}{2}, 1 + n\frac{\Delta y}{2})$, $m = 1 \dots M - 1$ and $n = 1 \dots N - 1$. Should the minimum eigenvalue over the whole image, $\lambda_{\min} = \min_{\mathbf{p} \in \Omega_P}(\lambda(\mathbf{p}))$ be less than the strain threshold τ , $\mathbf{p}$ and the corresponding displacement $\mathbf{u}_{PI}(\mathbf{p})$ are added to the lists ι_p and ι_d respectively. The data in these lists will be used to transfer the estimated tear to Ω_I . From this point of maximum strain, the tear is propagated along the two directions, $\mathbf{n}$ and $-\mathbf{n}$, normal to the direction of maximum strain $\mathbf{v}$ to a new point $\mathbf{p}'$. If $\lambda(\mathbf{p}') < \tau$ the lists ι_p and ι_d are updated and the next step will be in the corresponding new direction $\mathbf{n}'$. When a point is reached where $\lambda \geq \tau$ the tear tracking process stops.

If we expect negligible deformations around the tear due to brain shift (for instance when registering images taken after craniotomy with images acquired after resection/retraction) this estimation of the tear will be quite reliable. Whenever there is a considerable brainshift as well, the tear estimation is more likely to be stuck in a local minimum or diverge from the real tear. To add some robustness to the detection of the tear and to reduce the importance of choosing a suitable τ we incorporate some a-priori information in the retraction estimation. A line originating from the tumor center t_c in the pre-operative image is fitted to the points in ι_p weighted by the amount of strain (minimum eigenvalue) at this point. Assuming we have a model of the tumor in Ω_P and may know the length of the retractor, the part of the line which is represented by the retractor can easily be estimated.

Because the tearing is calculated in Ω_P , it is also necessary to estimate the tear in Ω_I to enable calculations of U_{IP} using the bijective demons algorithm. We estimate the corresponding tear in Ω_I by fitting a line going through $u_{PI}(t_c) + t_c$ to the points $\iota_p(k) + \iota_d(k)$, $k = 1 \dots K$, where K denotes the number of points along the tear. The part of the lines which are estimated to be representing the retraction is embedded in the boundary map Φ and transferred into directional boundaries by applying Eqs. (8)-(9). The algorithm then proceeds by alternating between registering the images and estimating the tear.

Determining the Retracted Area—Once a tear has been detected and added as a diffusion boundary, discontinuities will occur in both U_{PI} and U_{IP} . As the residuals, r_{PI} , in the bijective demons algorithm are computed in the pre-operative image domain, we will not see large residuals around the area of the tear (see Fig. 1). However, if the residual is computed in Ω_I , large residuals will appear in the area where tissue has been retracted. A simple thresholding scheme provides a good approximation of the area of retraction in the intra operative image.

$$\Gamma_I(\mathbf{x}) = \begin{cases} 1, & \text{if } r_{IP}(\mathbf{x}) > \frac{1}{N} \sum_{p \in \Omega_I} |r_{IP}^2(p)| \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

2.3 Modeling Resection

We wish to register a pre-operative image, P , with an intra-operative image, I , under the assumption that an area (volume in 3D) of tissue, $\Omega_{RP} \subset \Omega_P$ is present in P but is missing in I . The corresponding resected area in I will be denoted by $\Omega_{RI} \subset \Omega_I$. One can make a few assumptions about the areas Ω_{RI} and Ω_{RP} : 1) we will in general have large intensity disagreements $(I(\mathbf{x}) - (P \circ U_{IP})(\mathbf{x}))$, $\mathbf{x} \in \Omega_{RI}$ in the area of resected tissue, 2) large image gradients, ∇I , will be present along $\partial\Omega_{RP}$, the boundary of the resected tissue, 3) there might be some smaller image gradients inside Ω_{RI} due to blood or other fluids in the resected cavity, 4) image gradients in and around Ω_{RP} can be substantial due to a contrast enhanced tumor. These assumptions lead to unwanted forces being generated in and around Ω_{RI} and Ω_{RP} which will most likely lead the algorithm to converge to an incorrect result. Large image intensity disagreements are expected to be present inside the resected area which enables us to capture this area using a level set approach evolving in the space of image intensity disagreements. We incorporate Ω_{RI} and Ω_{RP} as diffusion sinks in the bijective demons approach. The general idea is to alternate between performing the registration under the constraint of the diffusion sinks and approximating the area of resected tissue with a level set formulation.

Determining the Resected Area—We are interested in propagating a front $\eta(t) \subset \Omega_I$ in time along its normal direction $\mathbf{n}$ until it embeds Ω_{RP} . In the level set formulation [11] this is achieved by embedding the front, η , as a zero level set of a time varying higher dimensional function

$$\varphi(\mathbf{x}, t) = \text{dist}(\mathbf{x}, \eta(t)), \mathbf{x} \in \Omega_t \quad (14)$$

where the function *dist* computes the signed distance *d* from $\mathbf{x}$ to the front η . If $\mathbf{x}$ is inside the front then $d < 0$ and if $\mathbf{x}$ is outside the front, $d > 0$. Let us define the label map

$$\Psi_t^k(\mathbf{x}, t) = \begin{cases} 1, & \varphi(\mathbf{x}, t) \leq k, \mathbf{x} \in \Omega_t \\ 0, & \varphi(\mathbf{x}, t) > k, \mathbf{x} \in \Omega_t \end{cases} \quad (15)$$

where Ψ_t^0 labels all pixels within the front as 1 (resected) and all pixels outside the front as 0 (non-resected) at time *t*. We will denote the area where $\Psi_t^k(\mathbf{x}, t) = 1$ by $\Omega_{\eta(t)}^k$. The level set function evolves according to the partial differential equation

$$\varphi_t = b\kappa|\nabla\varphi| - a|\nabla\varphi|. \quad (16)$$

On the right hand side we have two terms. The first term moves the front proportional to its curvature while the second term moves the front in the normal direction with a speed and direction determined by *a*. To maintain the property of ϕ being a distance function, it is necessary to reinitialize the levelset function using Eq. (14) at regular time intervals. We are interested in $\Omega_{\eta(t)}^k$ being the best possible approximation of the resected area, Ω_{R_I} , at every step of the algorithm. To achieve this we model the normal velocity of the front as

$$a(\mathbf{x}) = (1 - \Gamma_I(\mathbf{x}))|I(\mathbf{x}) - (\mathbf{P} \circ \mathbf{U}_{I_P})(\mathbf{x})|e^{-|\nabla I|/\sigma} - \rho, \mathbf{x} \in \Omega_t. \quad (17)$$

The middle term makes the interface expand fast where there is a large intensity disagreement, the exponential will effectively stop the propagation of the front at large gradients (such as at $\partial\Omega_{R_I}$). Due to the exponential, the evolution of the front will stop right before reaching $\partial\Omega_{R_I}$ hence Ψ_t^0 will consistently underestimate the real resection. We use Ψ_t^1 as the estimate of Ω_{R_I} . After the levelset evolution converges for the first time we will most likely have $\Omega_{\eta(t)}^1 \supset \Omega_{R_I}$. As the algorithm progresses, more and more of $\Omega_{\eta(t)}^1 \setminus \Omega_{R_I}$ will find its corresponding area in the pre-operative image and result in a good image intensity agreement.

This requires the front to shrink in this area to relabel it as non-resected which is modeled by ρ . The first term becomes zero in the area of retraction where we want the front to contract. It is important to balance the magnitude of ρ versus the magnitude of the intensity difference term such that a large intensity disagreement results in a positive *a*, while a good agreement results in a negative *a*.

Registration Constrained by a Diffusion Sink—In the classical demons method, the computed forces are diffused over the whole image domain. Whenever unwanted or incorrect image forces occur due to for instance resection, they will be propagated throughout the image by the Gaussian filter which will result in an incorrect deformation field. To prevent the forces occurring on and within $\partial\Omega_{R_I}$ from being diffused into the non-resected areas we use an over-

estimation of the resected area, Ψ_I^3 , as a diffusion sink in the smoothing component of the registration.

Because of the dual nature of the bijective demons method, the label map $\Psi_I^k(\mathbf{x})$ also needs to be defined in $\mathcal{Q}_P$:

$$\Psi_P^k(\mathbf{x}) = (\Psi_I^k \circ U_{PI})(\mathbf{x}). \quad (18)$$

The directional diffusion boundaries in both image domains are computed by Eqs. (10)-(11).

2.4 Algorithm

To capture large deformations and speed up the algorithm, the registration method was integrated in a 3-level multi-resolution pyramid with a subsampling factor of 2. Modeling of retraction and resection was only applied on the lowest level of the pyramid while the two higher levels were used to get a good initial non-rigid deformation field. The algorithm applied to the lowest level of the pyramid can be summarized as follows:

Initialize the levelset function with Eq. (14) and the initial front $\eta(0)$.

while $\Sigma_{\mathbf{x}}(\mathbf{I}(\mathbf{x}) - \mathbf{P} \circ U_{IP}(\mathbf{x}))^2 > \text{SSD Threshold}$ **do**

 Propagate tear as explained in Sec. 2.2.

 Evolve the levelsets using Eqs. (16) and (17).

 Extract resected area using Eqs. (15) and (18).

 Compute $B_{E|W|MS}$ according to Eqs. (8)-(11).

 Calculate U_{PI}^i and U_{IP}^i using the bijective demons and Eq. (6).

end while

3 Results

In this section we present preliminary results from applying the algorithm on 2D image data. All images used to generate results had a resolution of 256×256 with pixel intensities in the interval $[0, 1]$. The level set parameters, $b = 0.2$, $\rho = 0.1$ and $\sigma = 0.01$, diffusion filter parameters, $\mu = 0.2$, and $\eta = 170$ and strain threshold, $\tau = -0.4$, were applied for all experiments.

3.1 Experiments on Synthetic Data

To facilitate quantitative evaluation of how the algorithm handles both resection and retraction an artificial data set with a known deformation field was generated. The deformation field U_{IP} was generated by defining the displacements occurring on $\partial\mathcal{Q}_{RI}$ and $\partial\mathcal{Q}_{TI}$, where $\mathcal{Q}_{TI}$ is the area of tearing in $\mathcal{Q}_I$, and then applying the smoothing filter with diffusion boundaries preventing diffusion into $\mathcal{Q}_{RI}$ and $\mathcal{Q}_{TI}$. A displacement of magnitude 4 in the direction of the retracted area was defined on $\partial\mathcal{Q}_{TI}$ while the displacement on $\partial\mathcal{Q}_{RI}$ was set to 3 in the direction normal to the boundary. In addition, a displacement of about 6 pixels due to brain shift was also simulated. Fig. 3 shows both the resulting dataset as well as the qualitative results of the registration. We computed the dice coefficient between the estimated labelmaps Ψ_P , Ψ_I and Γ_I and the real labelmaps used to generate the synthetic dataset which resulted in the values 0.93, 0.94 and 0.91 respectively.

3.2 Experiments on Clinical Data

The algorithm was also tested on a set of clinical T1 MRI data acquired from a neurosurgical procedure where retraction was necessary to perform the resection. First the pre-operative and intra-operative datasets were rigidly registered. Two corresponding slices were extracted along the retraction line and a manual skull stripping procedure was performed. The two slices can be seen in Fig. 4 together with the qualitative results which were achieved.

4 Discussion

In this paper we have proposed a registration framework which can handle retraction and resection. The main contributions are the detection of tearing of the deformation field due to retraction, and detection of missing tissue due to resection as well as how to model these in the demons algorithm. We have shown the framework's applicability on both synthetic and clinical image data.

A few parameters need to be specified for the algorithm to work properly. Two parameters are exposed by the smoother, but none of them are directly data-dependent. The number of diffusion iterations mimics the standard deviation of the Gaussian filter applied in the traditional Demons method. To achieve more smoothing one needs to increase the number of diffusion iterations, or equivalently increase the standard deviation of the Gaussian smoothing filter. To achieve a stable solution of the diffusion equation the step length should be $\mu < 0.25$. Both the detection of retraction and resection exposes data-dependent parameters. In the case of retraction, the algorithm is quite sensitive to the specific value of τ . If it is too low, no retraction line is detected but if it is set too high a too long retraction line is detected. However, with the inclusion of the a-priori information regarding the tumor center and the length of the retractor the algorithm is considerably less sensitive to the specific value of τ . In the specification of the normal velocity of the front for the level set formulation, one has to specify the parameter ρ . This parameter defines what intensity difference is acceptable and has to be balanced according to the magnitude of the intensity differences which can occur.

Our current implementation of the framework is limited to 2D, but we see no big obstacles in extending it to 3D. Because of the current dimensionality constraint we had to extract two corresponding slices from two 3D data sets to construct the clinical data. We acknowledge that there might be out of plane deformations which we have not accounted for in the slice extraction process.

Using a Matlab implementation and a Dual Core 2.16 GHz processor, about 20 min of computational time was required to run 100 iterations on each level. Solving the anisotropic diffusion equation is by far the slowest part of the algorithm, but considerable speedups can be achieved by parallelizing the computations by utilizing GPGPU methods or multi-core processors.

Acknowledgments

This work was supported by NIH grants U41RR019703 and P41RR13218.

References

1. Hartkens T, Hill DLG, Castellano-Smith AD, Hawkes DJ, Maurer CR, Martin AJ, Hall WA, Liu H, Truwit CL. Measurement and analysis of brain deformation during neurosurgery. *IEEE Transactions on Medical Imaging* 2003;22(1):82–92. [PubMed: 12703762]
2. Periaswamy S, Farid H. Medical image registration with partial data. *Medical Image Analysis* 2006;10:452–464. [PubMed: 15979375]

3. Miga MI, Roberts DW, Kennedy FE, Platenik LA, Hartov A, Lunn KE, Paulsen KD. Modeling of retraction and resection for intraoperative updating of images. *Neurosurgery* 2001;1(1):75–85. [PubMed: 11440463]
4. Thirion JP. Image matching as a diffusion process: an analogy with Maxwell's demons. *Medical Image Analysis* 1998;2(3):243–260. [PubMed: 9873902]
5. Hellier P, Barillot C, Corouge I, Gibaud B, Le Goualher G, Collins DL, Evans A, Malandain G, Ayache N, Christensen GE, Johnson HJ. Retrospective evaluation of intersubject brain registration. *IEEE Trans Med Imaging* 2003;22(9):1120–1130. [PubMed: 12956267]
6. Cachier P, Bardinet E, Dormont D, Pennec X, Ayache N. Iconic feature based nonrigid registration: the pasha algorithm. *Comput Vis Image Underst* 2003;89(2-3):272–298.
7. Perona P, Malik J. Scale-space and edge detection using anisotropic diffusion. *IEEE Trans Pattern Anal Mach Intell* 1990;12(7):629–639.
8. Alvarez L, Deriche R, Papadopoulos T, Sánchez J. Symmetrical dense optical flow estimation with occlusions detection. *Int J Comput Vision* 2007;75(3):371–385.
9. Noblet V, Heinrich C, Heitz F, Armspach JP. 3-D deformable image registration: a topology preservation scheme based on hierarchical deformation models and interval analysis optimization. *IEEE Transactions on Image Processing* 2005;14(5):553–566. [PubMed: 15887550]
10. Müller, M.; McMillan, L.; Dorsey, J.; Jagnow, R. *Proceedings of the Eurographic workshop on Computer animation and simulation*. Springer; New York: 2001. Real-time simulation of deformation and fracture of stiff materials; p. 113-124.
11. Osher, SJ.; Fedkiw, RP. *Level Set Methods and Dynamic Implicit Surfaces*. Springer; Heidelberg: 2002.

Fig. 1.

Whenever an area in Ω_P is found where the strain in the deformation field exceeds a certain threshold, this point is added as boundary in the smoother to enable a discontinuity to develop in Ω_P . This can be seen in the *left* figure. At the same time, the corresponding boundary is placed in Ω_I which is shown in the *right* figure. Notice that the residual r_{IP} will be very large at the areas of retraction, something which can be effectively used to approximate the width of the retracted area.

Fig. 2.

The *left* plot shows three different compartments, each having a mean value of $y = 6, 2, 10$ with uniform noise added to it. One approach for modeling diffusion here would be to add diffusion boundaries between the compartments. The *middle* plot includes the results from running this through the diffusion filter ($\eta = 100, \mu = 0.2$). Notice that values have effectively been confined to their respective compartments which has resulted in discontinuities at the boundaries. We will use this concept for modeling retraction. Another approach is to model the middle compartment as a diffusion sink which allows diffusion into the compartment but not out of it. The *right* figure shows results from running the diffusion filter on this case. Notice the continuous values across the boundaries between the compartments and that none of the information from the middle compartment has diffused into the two neighboring compartments.

Fig. 3.

[a b c d; e f g]: The top row shows [a] the pre-operative image, [b] the synthetically deformed image and [c]- [d] the estimated x - and y -components of the deformation field. [e] shows the deformed pre-operative image (with the estimated Ψ_I and Γ_I zeroed out), [f] the difference image in $\mathcal{Q}_I$ and [g] the pre-operative image with the estimated resected area highlighted.

Fig. 4.

[a b c d; e f g]: In [a] we have pre-operative image, [b] the intra-operative image, [c]- [d] the estimated x - and y - components of the deformation field U_{IP} , [e] the deformed pre-operative image $P \circ U_{IP}$ after masking out the estimated resected and retracted areas, [f] the difference image $|I - P \circ U_{IP}|$ after masking out the estimated retracted and resected areas and [g] the pre-operative image with the estimated resected area highlighted. From these qualitative results we can see that the algorithm provides fairly good estimates of both the retracted and resected areas.