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Vessel to Image Registration using Rigid and Elastic Transformations

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Abstract. Several recent studies demonstrate a real potential in taking tubular structures as a base for image registration. In this paper, we present a novel technique to conduct deformations on tubular structures. Our approach aligns a pre-extracted tubular model, e.g. vessels inside an organ or a set of bones, with an image by combining both rigid and elastic transformations. The physical structure and properties of the tubes are taken into account to drive the registration process. This model to image registration shows sub-voxel accuracy as well as robustness to noise and a convergence time of less than one minute.

1 Introduction

We present a novel technique to perform model-to-image registration using tubular structures as a model. Our approach uses both rigid and deformable transformations in a hierarchical manner. Our technique takes advantage of the typical tree structure of blood vessels and uses branch points to constrain deformations. We perform three distinct steps to achieve final registration of the model with the image: global rigid transformation, piece-wise rigid registration and deformable registration. The first stage deals with the global rigid body registration and has been shown to be sub-voxel accurate, able to handle large initial mis-registrations and converge in 2-10 seconds [1]. Such rigid registration is a preliminary and necessary stage in order to be close enough to the deformed structure. One could notice that the rigid registration algorithm does not take advantage of the tree structure and, therefore, uses the set of tubes as a global entity. The second stage uses the tree structure to perform a piece-wise rigid alignment. First, the root of the tree is moved to the right position and then rigid transformations are applied, in order, from root to leaves. Branch points and physical parameters of the tubular structure have to be known to perform this task. Local deformation is the concern of the third and last stage.

Mutual information and several related techniques register one image to another and use, in most cases, a rigid or an affine transformation [4], although, non-rigid versions also exist [5]. Aylward et al. [1] have demonstrated that rigid registration of vessels with an image can be performed quickly and with reasonable accuracy. However, due to the elastic properties of organs, rigid transformation is often not enough. Fluid based registration approaches take into account the deformable aspect of the registration but do not take advantage of the geometry of the objects in the images. On the other hand, model-to-model registration techniques have been developed and exploit the geometric correspondences in a powerful manner. Finite element modeling also shows excellent results [3] by deforming a mesh given image forces. Our technique differs from these approaches by combining both rigid and deformable transformations and geometry and intensity information and falls into the model-to-image registration category.

2 Method

Blood vessels in the human body are organized as a tree structure. For instance, in the liver, portal and hepatic vessels define two distinct trees; in the brain, vessels are divided into several trees, among them, the right and left cerebral group. Formally, a tree is composed of at least one root. Our technique relies on this tree configuration to perform a global to local registration. The first step is a global rigid body registration using a vessel-based metric and a gradient descent optimization process [1]. The second step consists of a piece-wise rigid registration from root to leaves. The third step is done via non-rigid deformation of the vessels. These two last steps are described next.

2.1 Piece-wise rigid transformation via propagation

A rigid transformation is applied to each vessel in a hierarchical manner. First the root of the tree is registered with the image using a rigid body transformation. Second, the branches of the tree are registered rigidly with the image one branch at a time using the parent-child hierarchy which gives anchor points, namely branch points. We allow rotation around the branch point. The magnitude of the rotation is given by the gradient $\boldsymbol{\nu}$ computed along the branch only (its descendants do not contribute). The evaluation of the rotation is done using a linear weighted factor $\lambda(i)$ along the tube so that points at index i close to the branch contribute more to the rotation. The image gradient is computed only at centerline points x at a scale σ proportional to the radius of the tube at that point. N represents the number of centerline points that compose the vessel. For each point the image gradient is projected onto the normal plane $\boldsymbol{n_1}$,$\boldsymbol{n_2}$.

$$\boldsymbol{\nu} = \frac{1}{N} \sum_{i=1}^{N} \lambda(i) \boldsymbol{\nabla}_{\boldsymbol{x}}(\sigma) \cdot \boldsymbol{n} \tag{1}$$

Rotations and translations for the branch are solved iteratively via calculations of $\boldsymbol{\nu}$. One could notice that $\lambda(i)$ is important to obtaining a good combination of translation and rotation.

To translate a branch, the elastic property of the parent has to be taken into account. Specifically, the translation vector $\boldsymbol{\nu}$ of the child is projected onto the tangent direction $\boldsymbol{t}$ of its parent at the specified branch point x and the amount of translation $\boldsymbol{T}$ allowed from the initial point x_0 is constrained by the elasticity γ of the parent tube multiplied by the initial distance d between the two consecutive points near the branch. The translation is only permited in the direction of $\boldsymbol{t}$.

$$\boldsymbol{T} = \max(\boldsymbol{\nu} \cdot \boldsymbol{t}, \gamma d - |x - x_0|) \cdot \boldsymbol{t} \tag{2}$$

2.2 Elastic registration

Elastic registration is also performed using first derivative information from the target image. Our approach uses the image gradient computed at a scale proportional to the radius of the tube and projected onto the normal of the tube (like 2.1). Due to the potential complexity of the elastic deformations, i.e. folding, shrinking, expansion, etc., we must add constraints to drive the registration process. The first constraint is the elasticity coefficient γ of the tube which constrains the movement of points along a tube (as in 2.1). The second constraint is the rigidity coefficient which defines the bending factor of the tube. There are several ways to define such a coefficient and we use a local measure; rigidity is defined as the maximum angle between the initial tangent $\boldsymbol{t_0}$ and the actual tangent $\boldsymbol{t}$. The rigidity coefficient can be different for each point along the structure, or it can be constant. The rigidity of the tube is proportional to the radius of the tube and depends also on the material. In our implementation we choose to keep the rigidity constant and we use the sampling rate to accomodate the coefficient as the radius is changing. In fact, as a pre-process, the tubular model is sampled, for speed optimization purposes, in a non-uniform manner so that the step size depends on the radius value at the previous centerline point.
An iterative optimization process uses these two coefficients, and the projected gradient is computed for each point along the centerline to deform each branch to the data. The process of rigid and deformable registration is then applied to each of its leaves. This continues until the full hierarchy has been fit to the data.

3 Results

In order to evaluate the accuracy of our registration algorithm we extract blood vessels from the target image. It is important to note that these vessels are not used in the registration process, but only for validation purposes. We have run our algorithm on pre and post surgery brain data in which a tumor has been removed. An initial global rigid body registration is performed [1]. Fig.1-left shows the result. Next we apply 40 piece-wise rigid transformation iterations per branch, Fig.1-right. Fig.2 shows the final registration using both piece-wise rigid and elastic transformations. Both stages of the elastic registration requires less than 10 seconds to converge.

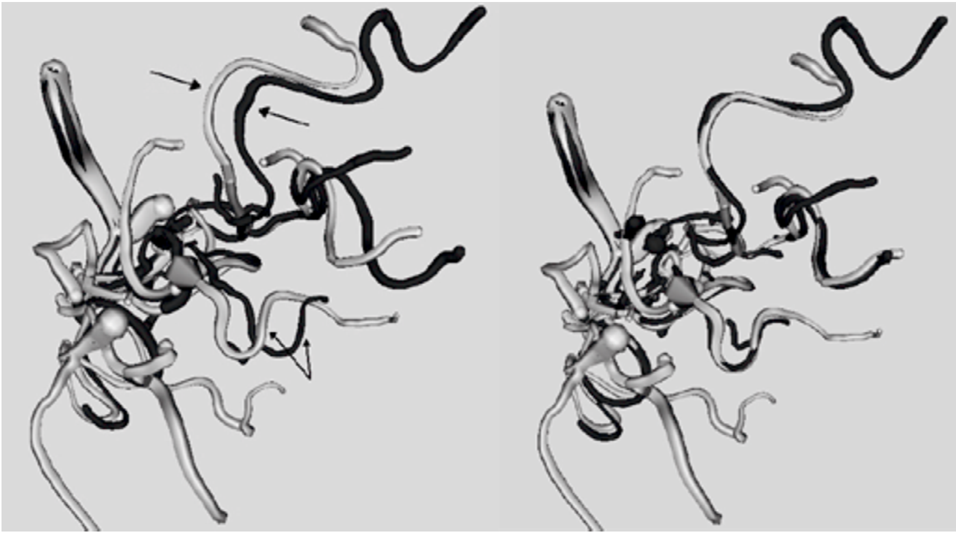

Fig. 1. Original set of tubes registered with a global rigid transformation(left) and the resulting set of tubes after the piece-wise rigid registration(right). Only the black vasculature is moving. The light grey vasculature is shown here as an illustration but is never used to drive the registration process. The data that produced those light grey tubes is actually driving the registration process

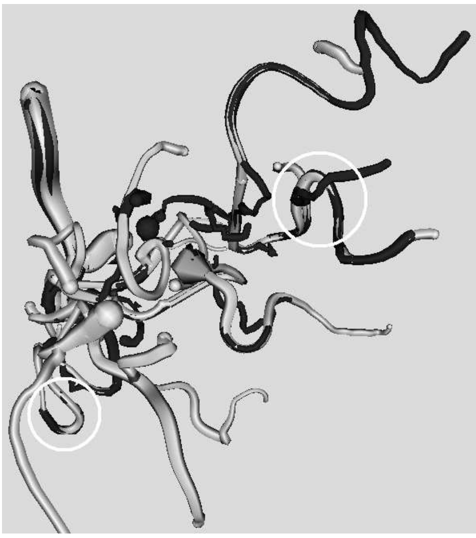

Fig. 2. Set of tubes after the deformable registration process. Elastic deformations are applied after the semi rigid registration. Again, the light grey vasculature is shown here as an illustration but is never used to drive the registration process. Circles highlight areas of larger non-rigid deformation

The quantification of the registration is shown on Figure 3.

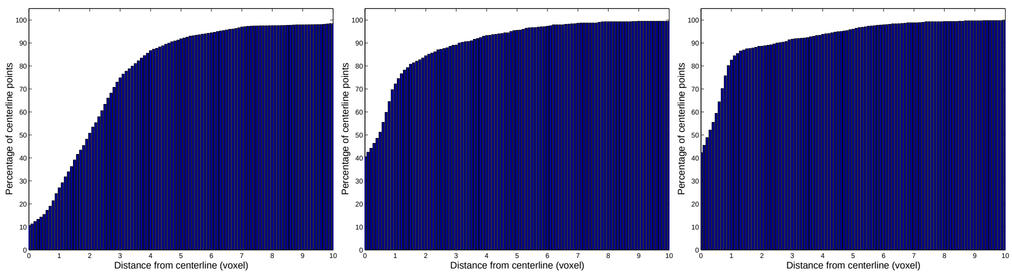

Fig. 3. Percentile of points inside a given distance from the centerlines of the vessels in the target image (cumulative graphs). Before registration(left), after semi-rigid registration(middle) and after semi-rigid plus elastic registration(right)

Our method has also been tested on simulated data to perform noise sensitivity measurements. Figure 4 shows the three consecutive steps of the algorithm, after rigid registration(left), after piece-wise rigid transformations(middle) and after elastic registration(left).

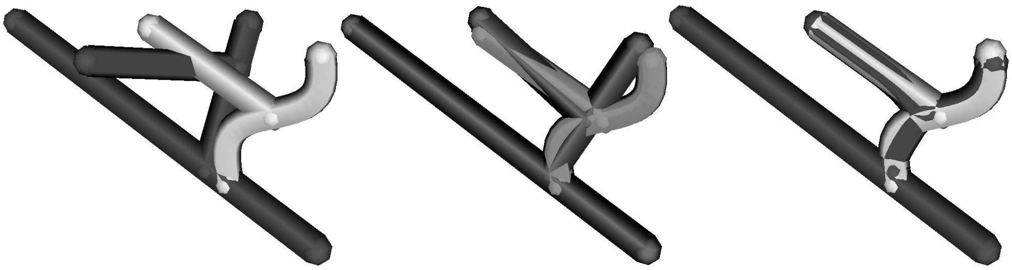

Fig. 4. Simulated tubes used to test the robustness of our algorithm. Original sets of tubes(left), After semi-rigid registration(middle) and after elastic registration(right). Only the light grey tubes are moving and the dark ones are represented for illustration

Figure 5 shows the cumulated measures of the percentile of points inside a given distance from the centerline without noise

Table 6 demonstrates the robstuness of our algorithm given different ranges of additive noise level. Even when the noise is in the same range as the image, the accuracy of the registration process shows a fall-off of 3.5% only.

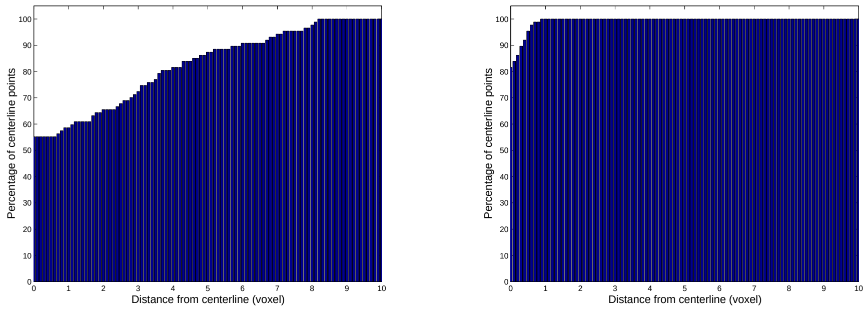

Fig. 5. Cumulative graphs representing the percentile of points of the whole vasculature inside a certain distance from the centerline for the simulated data, before registration(left) and after rigid and elastic transformations(right)

Noise level range	% of points $\leq$ 1 voxel	% of points $\leq$ 2 voxels	% of points > 2 voxels
[0,0]	100 %	100 %	0 %
[0,50]	100 %	100 %	0 %
[0,100]	97.7 %	100 %	0 %
[0,200]	96.8 %	99.7 %	0.3 %
[0,255]	96.5 %	99 %	1 %

Fig. 6. Influence of different additive white noise levels on the registration process

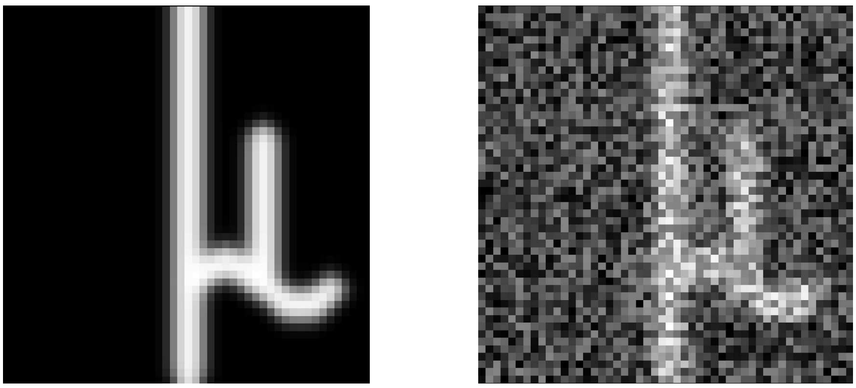

Fig. 7. Simulated images, with no noise(left) and with a noise range [0,255](right), used to test the robustness to noise of our algorithm.

4 Discussion and Conclusions

We have developed a model to image registration technique that uses both rigid and deformable transformations. Our model, a set of blood vessels, is registered with a 3-dimensional image. Our method exploits the hierarchy of tubes and consider their elasticity and flexibility. It is shown to operate with $\approx 87\%$ of centerline points within 2 voxels on pre-post surgery MRI.

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