A New Class of Distance Measures for Registration of Tubular Models to Image Data

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Abstract. In some registration applications additional user knowledge is available, which can improve and accelerate the registration process, especially for non-rigid registration. This is particularly important in the transfer of pre-operative plans to the operating room, e.g. for navigation. In case of tubular structures, such as vessels, a geometric representation can be extracted via segmentation and skeletonization. We present a new class of distance measures based on global filter kernels to compare such models efficiently with image data. The approach is validated in a non-rigid registration application with Powerdoppler ultrasound data.

1 Introduction

The importance and clinical use of 3D planning systems [1] in liver surgery is increasing. First navigation systems based on intra-operative 3D ultrasound have been developed and clinically applied [2]. Until now the transfer of pre-operative models and plans to the patient in the operating room (OR) is mentally performed by the surgeon. Robust and fast methods are needed for a precise multimodal non-rigid registration of the pre-operative data and the intra-operative 3D ultrasound image volume.

Although efficient implementations of parametric (multilevel B-splines) [3] as well as non-parametric [4] non-rigid image-based registration methods have been developed they are still very time-consuming for the intra-operative use. Only few papers and only for rigid transformations have been published regarding multi-modal registration of ultrasound with CT/MR data [5].

One of the main building blocks of a registration method is a suitable distance measure. The focus of this paper is on the definition of a new distance measure. Different distance measures for multi-modal registration have been published. These measures assume a functional (Correlation Ratio) [5], statistical (Mutual Information) [6] or locally affine relationship (Local Correlation Coefficient) [7] between the template and reference intensity values of corresponding image points. On the contrary Haber et al. [8] (Normalized Gradient Field) and Droske et al. [9] used measures based on the morphology of the image data to be independent of the actual intensity values.

The incorporation of previous knowledge about the characteristics of the imaging modality or the geometry of relevant anatomical structures potentially leads to a more robust and efficient registration process. Henn et el. [10] suppress a known unwanted area (a lesion) in their distance measure. A more general formulation of weighted distance measures based on user-defined masks is presented by Schumacher et al. [11].

The idea of our approach is to incorporate previous knowledge in terms of extracted vessel models from pre-operative data and their special tube-like structure. In a typical computer-assisted liver surgery planning process the vessels are segmented from CT/MR data and the one-dimensional set of vessel center lines $C \subset \mathbb{R}^3$ are explicitly extracted via skeletonization. A hybrid distance measure comparing this data directly with intra-operative intensity data is proposed. It is based on the work of Aylward et al. [12], where a measure is presented which evaluates the response of a local Gaussian filter at each point on vessel center lines. The sum of all these filter responses is maximized assuming a high response in the presence of a vessel in the intra-operative data. However, this approach fails for non-rigid registration. Therefore, we reformulate the presented measure (section 2) and improve it by using a more appropriate vessel detecting filter class (section 3). The approach is validated in a non-rigid registration application with Powerdoppler ultrasound data (section 4).

2 Variational reformulation of Aylward's distance measure

The new distance measure is formulated in the parametric variational registration framework, but it is equally suitable for non-parametric approaches. We reformulate Aylward's measure in this framework to illustrate similarities and differences to the new measure.

Let $\Omega \subset \mathbb{R}^3$ be the image domain. For a reference image $\mathbf{R} : \Omega \to \mathbb{R}$ and a template image $\mathbf{T} : \Omega \to \mathbb{R}$ a parametric transformation $\varphi_\mathbf{a} : \mathbb{R}^3 \to \mathbb{R}^3$ is sought, which minimizes the following functional by deforming $\mathbf{T}$:

$$J(\mathbf{R}, \mathbf{T}; \mathbf{a}) = D(\mathbf{R}, \mathbf{T}(\varphi_\mathbf{a}(\mathbf{x}))) \to min \qquad (1)$$

In the case of the well-known B-spline approach [3], the parameters $\mathbf{a}$ are the positions of the control grid points. The distance measure D determines the similarity between $\mathbf{R}$ and $\mathbf{T}$. In the following the abbreviation $\mathbf{T}_\mathbf{a}(\mathbf{x}) := \mathbf{T}(\varphi_\mathbf{a}(\mathbf{x}))$ is used. For efficiency reasons, the pre-operative CT/MR data is chosen as reference $\mathbf{R}$ and the intra-operative Powerdoppler ultrasound data as template $\mathbf{T}$. The clinically relevant deformation from $\mathbf{T}$ to $\mathbf{R}$ is computed subsequently by inverting $\varphi_\mathbf{a}$.

Let $r : C \to \mathbb{R}^+$ denote the radius and $\mathbf{t} : C \to \mathbb{R}^3$ the tangential direction of the pre-operatively generated vessel center lines C. The idea of Aylward et al. is to determine a filter response at each point of the center lines and to integrate all those filter responses: the image data is locally convolved with a Gaussian kernel adapted to the radius r at this point. The presented distance measure can be formulated essentially (neglecting additional weighting) as:

$$D_G[C(\mathbf{R}), r(\mathbf{R}), \mathbf{T}; \mathbf{a}] = -\int_C \int_\Omega G(\mathbf{x}-\mathbf{y}, r(\mathbf{y}))\mathbf{T}_\mathbf{a}(\mathbf{x})\, d\mathbf{x}\, d\mathbf{y} \tag{2}$$

with $G(\mathbf{x}, \sigma) = e^{-\frac{\mathbf{x}^T\mathbf{x}}{2\sigma^2}}$.

The order of integration can be exchanged. Instead of convolving all points $\mathbf{y} \in C$ on the vessel center lines with a local kernel G all local kernels can be integrated first and then the resulting global kernel

$$\mathbf{P}_G(\mathbf{x}) = \int_C G(\mathbf{x}-\mathbf{y}, r(\mathbf{y}))\, d\mathbf{y} \tag{3}$$

can be multiplied with the template $\mathbf{T}$. Thus, we may re-parameterize the distance measure D_G in terms of a global kernel P_G

$$D(\mathbf{P}_G, \mathbf{T}; \mathbf{a}) = -\int_\Omega \mathbf{T}_\mathbf{a}(\mathbf{x})\mathbf{P}_G(\mathbf{x})\, d\mathbf{x} \tag{4}$$

such that the expressions $D_G[\,\cdot\,]$ of (2) and $D(\,\cdot\,)$ of (4) are equal. This implies that the global kernel $\mathbf{P}_G$ can be computed pre-operatively and only the cross correlation of $\mathbf{P}_G$ and the template image $\mathbf{T}$ has to be determined intra-operatively in each iteration of the registration.

Although the Gaussian filter G not only gives high responses to tube-like structures but also to other bright structures, the measure is shown to work quite well on the data of Aylward et al. However, the distance measure is inappropriate for non-rigid registration. Optimizing the deformation of the data leads to an enlargement of the vessels and thus in an increase of bright voxels until, after few optimization steps, the image is completely bright.

3 New distance measure based on vesselness filter

To overcome the drawback of the approach of Aylward et al. we propose to use filter kernels, which give high responses for tube-like structures of similar radius and direction. A similar kind of vesselness filter was published for example by Frangi et al. [13]. They analyze the eigenvalues $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$ of the Hessian matrix $\mathbf{H}$ for each voxel. The eigenvector $\mathbf{v}_1$ corresponding to λ_1 points in the direction of the vessel. For bright vessels on a dark background the eigenvalues have the property: $\lambda_1 \approx 0$ and $\lambda_1 \ll \lambda_2 \approx \lambda_3$. Frangi et al. define a scalar valued vesselness function depending on this property. Because the radii of the vessels are unknown, the vesselness response is calculated at multiple scales by computing the Hessian with Gaussian derivatives at multiple scales. At every voxel the vesselness value with the highest response is selected and the corresponding scale represents the radius of the vessel.

Since the vessels are parameterized explicitly by their radius and direction, so is the filter kernel. Let us define a local coordinate system at each center line point $\mathbf{y}$ by two normal directions $\mathbf{n}_1, \mathbf{n}_2 : C \mapsto \mathbb{R}^3$, $\mathbf{n}_1(\mathbf{y}) \perp \mathbf{n}_2(\mathbf{y})$, perpendicular to $\mathbf{t}(\mathbf{y})$. Motivated by the vesselness filters we define a filter kernel based on the sum of the second Gaussian derivatives in the two normal directions. This results in a Laplacian filter in the normal plane which is Gaussian weighted in the vessel direction. These second Gaussian derivatives

$$G_{\mathbf{xx}}(\mathbf{x}, \sigma) = \left(\frac{x^2}{\sigma^4} - \frac{1}{\sigma^2} \right) G(\mathbf{x}, \sigma) \tag{5}$$

are defined for $\sigma = \sqrt{2}r$, such that the zero crossings of the kernel are located at the vessel radius. The kernel has to be transformed to the position of a center line point $\mathbf{y}$ and orientation of the local coordinate system $\mathbf{z} = [\mathbf{t}, \mathbf{n}_1, \mathbf{n}_2]\,(\mathbf{x} - \mathbf{y})$. This yields the following filter kernel:

$$L(\mathbf{x}, \mathbf{y}, r, \mathbf{t}, \mathbf{n}_1, \mathbf{n}_2)) = G_{\mathbf{z}_2\mathbf{z}_2}(\mathbf{z}, r) + G_{\mathbf{z}_3\mathbf{z}_3}(\mathbf{z}, r) \tag{6}$$

and subsequently the global kernel

$$\mathbf{P}_L(\mathbf{x}) = \int_C L(\mathbf{x}, \mathbf{y}, r, \mathbf{t}, \mathbf{n}_1, \mathbf{n}_2)\; d\mathbf{y} \tag{7}$$

which replaces $\mathbf{P}_G$ in equation (4).

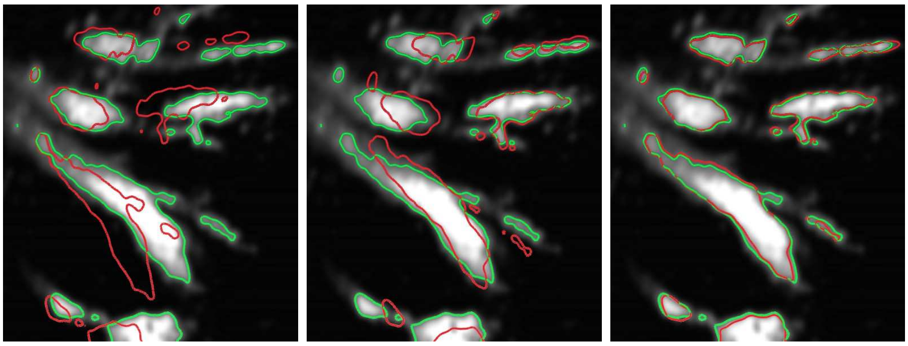
4 Results

In order to qualitatively validate the proposed distance measure we use the measure in a multilevel B-Spline scheme (without effective multi-resolution strategy) to register artificially deformed data. Vessel center lines are extracted with radii from real intra-operative 3D Powerdoppler ultrasound data. These center lines are deformed by a realistic B-spline deformation. The global kernel $\mathbf{P}_L$ is determined on the deformed center lines (Fig. 1a) and rigidly (Fig. 1b) resp. non-rigidly (Fig. 1c) registered. The deformation is substantially reduced and the original state is recovered well from a visual point of view. It cannot be expected that the original state can be perfectly reproduced by the registration algorithm, since segmentation, skeletonization and as well as radius computation introduce certain inaccuracies.

5 Discussion

We have re-parameterized the distance measure of Aylward et al. using a global kernel function. The latter can be computed pre-operatively and thus the distance measure can then be evaluated efficiently intra-operatively. This is an important aspect for non-rigid registration applications with tight time constraints. Furthermore we have derived a new distance measure suitable for comparing geometric representations of tubular structure with image data, as we have shown in a preliminary validation. Extended validation in more registration applications is in progress. Although we apply our method to tube-like features, the framework is general and we expect it to work also for other (e.g. plate-like) features. Such investigations are subject to future work.

Fig. 1. Powerdoppler ultrasound data of liver vessels with a) artificially deformed, b) rigidly and c) non-rigidly registered vessels



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