A distance measure for non-rigid registration of geometrical models to intensity data

1. Purpose

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.

The importance and clinical use of 3D planning systems [1] in liver surgery is increasing. First navigation systems based on intraoperative 3D ultrasound have been developed and clinically applied [2]. Until now the transfer of preoperative 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 multi-modal non-rigid registration of the preoperative data and the intraoperative 3D ultrasound image volume.

2. Methods

One of the main building blocks of a registration method is a distance measure suitable for the particular application. The idea of our approach is to incorporate user knowledge in terms of extracted vessel models from preoperative 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 $C \subset R^3$ are explicitly extracted via skeletonization. A hybrid distance measure comparing these features directly with intraoperative intensity data is proposed. It is based on the work of Aylward et al. [3], 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 2.1) and improve it by using a more appropriate vessel detecting filter class (section 2.2).

The new distance measure is formulated in the parametric variational registration framework [4], but it is equally suitable for non-parametric approaches [5]. Firstly Aylward's measure is reformulated in this framework to illustrate similarities and differences to the new measure.

2.1 Variational Reformulation of Aylward's Distance Measure

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

$$J(R,T;a) = D(R,T(\varphi_a(x)) \to \min \qquad (1)$$

In the case of the well-known B-spline approach [4], the parameters $\boldsymbol{a}$ are the positions of the control grid points. The distance measure D determines the similarity between $\boldsymbol{R}$ and $\boldsymbol{T}$. In the following the abbreviation $T_a(x) := T(\varphi_a(x))$ is used. For efficiency reasons, the pre-operative CT/MR data is chosen as reference $\boldsymbol{R}$ and the intra-operative Powerdoppler ultrasound data as template $\boldsymbol{T}$. The clinically relevant deformation from $\boldsymbol{T}$ to $\boldsymbol{R}$ is computed subsequently by inverting φ_a.

Let $r : C \to R^+$ denote the radius and $t : C \to R^3$ 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:

$$D_G[C(R), r(R), T; a] = -\int_C \int_\Omega G(x - y, r(y)) T_a(x) dx dy \qquad (2)$$

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

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

$$P_G(x) = \int_C G(x - y, r(y)) dy \qquad (3)$$

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

$$D(P_G, T; a) = -\int_\Omega T_a(x) P_G(x) dx \quad (4)$$

such that the expressions $D_G[.]$ of (2) and $D(.)$ of (4) are equal. This implies that the global kernel P_G can be computed pre-operatively and only the cross correlation of P_G and the template image 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.

2.2 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. [6]. They analyze the eigenvalues $\lambda_1 \le \lambda_2 \le \lambda_3$ of the Hessian matrix $\boldsymbol{H}$ for each voxel. The eigenvector 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 $\lambda_1 << \lambda_2 \approx \lambda_3$. 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 **y** by two normal directions $n_1, n_2 : C \to R^3, n_1(y) \perp n_2(y)$, perpendicular to $t(y)$. 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 [Fig 1]. These second Gaussian derivatives

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

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 **y** and orientation of the local coordinate system $z = [t, n_1, n_2](x - y)$. This yields the following filter kernel:

$$L(x, y, r, t, n_1, n_2) = G_{z_2 z_2}(z, r) + G_{z_3 z_3}(z, r) \qquad (6)$$

and subsequently the global kernel

$$P_L(x) = \int_C L(x, y, r, t, n_1, n_2) dy \qquad (7)$$

which replaces P_G in equation (4).

3. 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 and thereby the center line points are shifted by 4.5 (+/- 2.9) mm on average and maximally 9.6 mm. The global kernel P_L is determined on the deformed center lines (Fig. 2a) and rigidly (Fig. 2b) resp. nonrigidly (Fig. 2c) registered. The deformation is substantially reduced and the original state is recovered well from a visual point of view. We quantify the resulting deviations from the original and the registered vessels by computing the distance of corresponding center line points. After rigid registration a deviation of 3.3 (+/-0.2) mm on average and a maximum of 7.7 mm is left. After non-rigid registration the deviation is reduced to 1.0 (+/- 0.4) mm on average and a maximum of 2.3 mm. It cannot be expected that the original state can be perfectly reproduced by the registration algorithm, since segmentation, skeletonization and as well radius computation introduce certain inaccuracies.

4. Conclusion

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.

5. References

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Figures

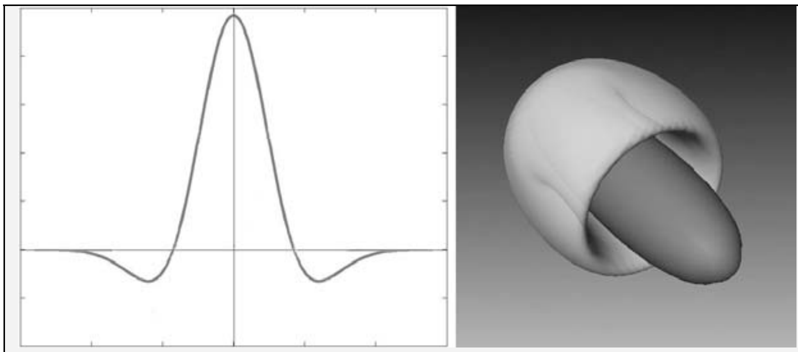

Fig. 1: Profile of second Gaussian derivative (left) and isosurface of local 3D vessel filter kernel with positive values (dark grey) inside and negative values (light grey) outside the vessel.

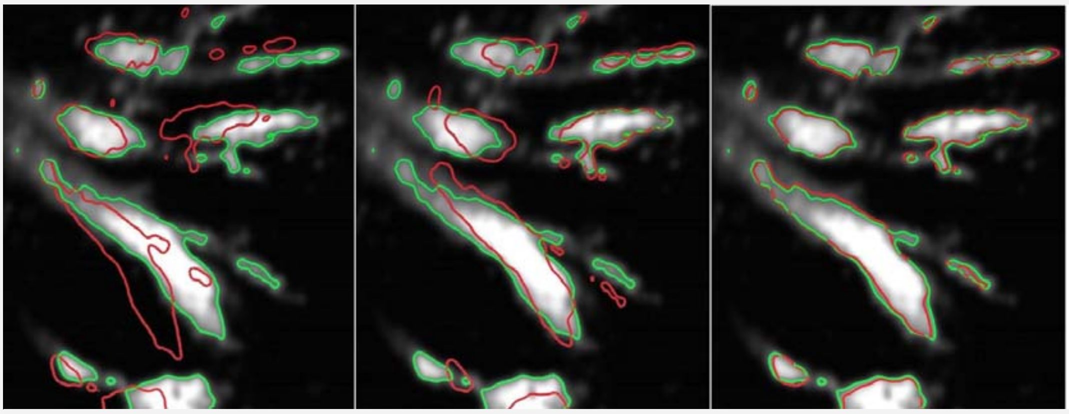

Fig. 2: Powerdoppler ultrasound data of liver vessels with a) artificially deformed, b) rigidly and c) non-rigidly registered vessels.