Local topology preservation for vascular centerline matching using a hybrid mixture model

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***Abstract*—Non-rigid registration is essential for a wide range of clinical applications, such as intraoperative image-guidance and postoperative follow-up assessment, and longitudinal image analysis for disease diagnosis and monitoring. Vascular structures are a rich descriptor of the organ deformation, since it permeates through all organs within body. As vasculature differs in size, shape and topology, following surgical intervention/treatment or due to disease progression, non-rigid vessel matching remains a challenging task. Recently, hybrid mixture models (HdMM) have been applied to tackle this challenge, and demonstrate significant improvements in terms of accuracy and robustness relative to the state-of-the-art. However, the smoothness constraint enforced on the deformation field with this approach only accounts for the global topology of the vasculature, resulting in a reduced capacity to accurately match localized changes to vascular structures, and preserve local topology. In this work, we proposed a modified version of HdMM by formulating an adaptive kernel, to enforce a local smoothness constraint on the deformation field, henceforth referred to as HdMMad. The proposed HdMMad framework is evaluated with cerebral and pulmonary vasculature, acquired retrospectively. The registration results for both data sets demonstrate that the proposed approach outperforms registration algorithms also designed to preserve local topology. Using HdMMad, around 80% of the initial registration error was reduced, for both data sets.**

I. Introduction

FOR numerous clinical applications, serially acquired intrapatient image data are commonly registered into a single coordinate frame for further analysis or decision making. As the vessels represent an intrinsic bio-marker that permeates through all organs, morphological changes to soft tissues caused by tissue manipulation or progression of chronic diseases, may be estimated by non-rigidly matching vasculature. Consequently, an accurate and robust alignment of vasculature benefits the quality of intrapatient image registration, for a broad spectrum of clinical procedures.

In [1], the authors categorize vascular registration techniques into point-, graph- and curve-based approaches. Compared to graph- and curve-based methods, point-based approaches do not require *a priori* identification of correspondences. Considering the registration of vasculature as a point matching problem of its centerline points, iterative closest point (ICP) can be used to establish the point correspondences between the target and source points [2]. Additionally, probabilistic approaches based on Gaussian Mixture Model (GMM) such as Coherent Point Drift (CPD) [3], has been applied e.g. for cerebral vessel alignment [4]. Compared to ICP, CPD demonstrates its superiority in medical image processing tasks. However, fundamental drawbacks of CPD in a clinical setting are the lack of inherent robustness to outliers, and the absence of local topology preservation. In order to confer localized robustness to the registration process, [5] proposed a point matching framework based on Student's t-distributions (TMM). Furthermore, a hybrid representation of vessel centerlines was proposed recently [6], resulting in increased discriminative capacity of the mixture models for deformable registration of cerebral vasculature. Local topology constraint inspired by Local Linear Embedding was incorporated into a GMM-based registration framework (GLTC) in [7]. Recently, a more sophisticated local topology constraint based on geodesic path (GLTCgeo) was proposed in [8], to quantify the changes in vascular morphology of lung diseases.

We present a hybrid mixture model for non-rigid registration, equipped with the functionality to preserve local vascular topology, in a manner robust to outliers. In contrast to our previous work [6], here we use a locally adaptive kernel derived from the hybrid mixture model parameters. The proposed framework is evaluated using cerebral and pulmonary vascular data, and compared with the state-of-the-art.

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II. Hybrid mixture model with adaptive local topology constraint

Vessel registration can be treated as the matching of vessel centerlines. With the HdMM approach [6], extracted centerlines are represented as 6-dimensional hybrid points, comprising spatial position and axis orientation. Registration of vessel centerlines is formulated as a probabilistic density estimation problem, where the hybrid points defining the `Source` are regarded as the centroids of the mixture model and the `Target` hybrid points are regarded as data points. The spatial positions are modeled using Student's t-Distributions ($\mathcal{S}$), while the axes orientations are modeled with Watson Distributions (refer to eq. 1). The `Source` is registered to the `Target` by iteratively maximizing the log-likelihood (*llh*) using the expectation maximization (EM) framework.

Watson distribution: The Watson distribution ($\mathcal{W}$) is a directional probability distribution with antipodal symmetry. This distribution is parameterized by the mean orientation $\mathbf{m}$ and the concentration κ, where κ is analogous to the precision of a Gaussian distribution.

$$p(\pm\mathbf{n}_i \mid \mathbf{m}_j, \kappa_j) = M(\frac{1}{2}, \frac{D}{2}, \kappa_j)^{-1} \exp^{\kappa_j (\mathbf{m}_j{}^T \mathbf{n}_i)^2} \quad (1)$$

Registration Framework: We assume the spatial position ($\mathbf{x}_i$) and centerline orientation ($\mathbf{n}_i$) components of each hybrid point in the `Target` set to be conditionally independent. Consequently, their joint probability density function (PDF) can be approximated as a product of the individual conditional densities. Considering all `Target` points to be independent and identically distributed (i.i.d), the objective function to be

TABLE I: Comparison of the accuracy of CPD, GLTC, GLTCgeo, HdMM, HdMMgl, HdMMgeo and HdMMad for cerebral and pulmonary vessel registration. Mean and standard deviation of all evaluation metrics in millimeters (mm) are presented.

		CPD	GLTC	GLTCgeo	HdMM	HdMMgl	HdMMgeo	HdMMad
Cerebral	MSD	2.36 ± 0.25	2.08 ± 0.46	2.37 ± 0.37	1.03 ± 0.23	1.03 ± 0.23	1.04 ± 0.23	$\mathbf{0.93 \pm 0.20}$
	MHD	2.49 ± 0.28	2.22 ± 0.39	2.59 ± 0.49	1.23 ± 0.31	1.23 ± 0.31	1.21 ± 0.30	$\mathbf{1.14 \pm 0.31}$
Pulmonary	MSD	3.42 ± 0.83	3.40 ± 0.83	3.57 ± 0.61	2.44 ± 0.57	2.44 ± 0.56	2.91 ± 0.41	$\mathbf{1.91 \pm 0.32}$
	MHD	3.80 ± 0.90	3.79 ± 0.91	3.90 ± 0.69	2.53 ± 0.54	2.53 ± 0.53	3.03 ± 0.41	$\mathbf{2.03 \pm 0.33}$

optimized with respect to the model parameters $\{\Theta_p, \Theta_n\}$ is defined as Eq. 2.

$$\log(\mathbf{T} \mid \mathcal{T}, \Theta_p, \Theta_n) = \sum_{i=1}^{N} \ln \sum_{j=1}^{M} \pi_j \mathcal{S}(\mathbf{x}_i \mid \mathcal{T}\boldsymbol{\mu}_j, \nu_j, \sigma^2) \mathcal{W}(\mathbf{n}_i \mid \mathcal{T}\mathbf{m}_j, \kappa_j) \tag{2}$$

Initially, an affine transformation ($\mathcal{T}$) and model parameters $\Theta_p = \{\nu_j, \sigma^2\}$ and $\Theta_n = \{\kappa_j\}$ associated with $\mathcal{S}$ and $\mathcal{W}$ are updated in the M-step similarly to [6]. Subsequently, the non-rigid deformation is estimated by maximizing Eq. 3, with respect to the associated parameters $\mathbf{W}$.

$$Q(\Theta_p^{t+1} \mid \Theta_p^t) = \sum_{i,j=1}^{N,M} -P_{i,j}^{\star(t)} \frac{||\mathbf{x}_i - (\boldsymbol{\mu}_j + v(\boldsymbol{\mu}_j)||^2}{2\sigma^2} + \frac{\lambda}{2} \mathrm{Tr}\{\mathbf{W}^T \mathbf{G} \mathbf{W}\} \tag{3}$$

Locally Adaptive Kernel: In Eq. 3, v is the desired displacement field, while $\mathbf{G}$ represents the Gaussian kernel, which regulates the smoothness of v. In CPD, the Gaussian kernel is defined as $G(\boldsymbol{\mu}_l, \boldsymbol{\mu}_m) = exp^{-\| \frac{\boldsymbol{\mu}_l - \boldsymbol{\mu}_m}{2\beta} \|^2}$, where β is used to control the width of the kernel, and consequently, the smoothness of v. As β is fixed and user-defined for all points μ, it requires prior information regarding the degree of smoothness required for a given task. Additionally, this enforces a global smoothness constraint on v. In our framework, we employ κ_j, derived from the initial affine registration to compute a locally adaptive Gaussian kernel as $G(\boldsymbol{\mu}_l, \boldsymbol{\mu}_m, \kappa_j) = exp^{-\|2\kappa_j(\boldsymbol{\mu}_l - \boldsymbol{\mu}_m)\|^2}$. Since κ_j is estimated automatically for each component of HdMM, the resulting G is inherently locally adaptive, which enables recovery of localized deformations and preserves local topology.

III. Experiments and Results

The proposed framework, HdMMad, is evaluated using two intra-patient datasets, namely, cerebral and pulmonary vasculature, for intraoperative guidance during tumour resection surgery, and assessing pulmonary disease-driven changes to vasculature, respectively. The voxel size of the cerebral and pulmonary images are 0.48mm^3 and $0.65 \times 0.65 \times 2.5$mm, respectively. The images were processed and hybrid point sets were generated as described in [6] and [8]. Overall, 6 pairs of cerebral vessel centerlines from a single neurosurgical procedure, and 8 random pairs of pulmonary vessel images from the SPREAD study [9], were used.

The effectiveness of the proposed adaptive Gaussian kernel is compared with state-of-the-art probabilistic approaches such as CPD, GLTC, GLTCgeo and HdMM proposed in [3], [6], [7], [8], respectively. In order to evaluate of the performance of HdMMad comprehensively, local topology constraints proposed the in [7] and [8] are combined with HdMM (henceforth referred as HdMMgl and HdMMgeo respectively), providing two additional benchmark methods.

Modified Hausdorff distance (`MHD`) [10], and mean surface distance (`MSD`) [5], are used to quantitatively assess registration accuracy. For a fair comparison, we set the λ to 1 and the number of EM-iterations to 100, for all experiments. For GLTC, GLTCgeo, HdMMgl and HdMMgeo, the hyperparameter α related to the local topology constraint is set to 100 and the width of Gaussian Kernel β is set to 1. The uniform distribution weight for CPD, GLTC and GLTCgeo are remained fixed to 0.5, for all experiments. The quantitative results are summarized in Table. I. The average `MSD` and `MHD` prior to registration for the cerebral and pulmonary vessel pairs are 5.40 ± 1.24mm, 5.62 ± 1.31mm, and 8.24 ± 2.33mm, 9.07 ± 3.7mm, respectively.

IV. Discussion and Conclusion

HdMMad, a vessel registration framework with a locally adaptive kernel was proposed in this study. The quantitative results indicate that the proposed framework consistently outperforms the state-of-the-art in all experiments. The locally adaptive nature of the proposed approach permits recovery of localized deformations more accurately, and enables better preservation of local topology, relative to its counterparts that employ a global smoothness constraint. Furthermore, only one user-defined hyperparameter remains in the proposed framework, in contrast to the others, which require multiple such parameters to be tuned for a given task. Automatic robustness to outliers, improved discriminative capacity, and the locally adaptive nature of the proposed registration framework, make it well suited to a variety of clinical applications.

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