Non-rigid multi-modal registration of coronary arteries using SIFTflow

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Abstract. The fusion of clinically relevant information coming from different image modalities is an important topic in medical imaging. In particular, different cardiac imaging modalities provides complementary information for the physician: Computer Tomography Angiography (CTA) provides reliable pre-operative information on arteries geometry, even in the presence of chronic total occlusions, while X-Ray Angiography (XRA) allows intra-operative high resolution projections of a specific artery. The non-rigid registration of arteries between these two modalities is a difficult task. In this paper we propose the use of SIFTflow, in registering CTA and XRA images. At the best of our knowledge, this paper proposed SIFTflow as a XRay-CTA registration method for the first time in the literature. To highlight the arteries, so to guide the registration process, the well known Vesselness method has been employed. Results confirm that, to the aim of registration, the arteries must be highlighted and background objects removed as much as possible. Moreover, the comparison with the well known Free Form Deformation technique, suggests that SIFTflow has a great potential in the registration of multimodal medical images.

1 Introduction

Chronic total occlusions (CTO) are obstructions of native coronary arteries with the presence of Thrombolysis In Myocardial Infarction (TIMI) flow grade 0 within the occluded segment, *i.e.* no blood flow, with an estimated occlusion duration of more than 3 months. Re-canalization of a CTO still remains a challenge for invasive cardiologists, due to the fact that the obstructed artery is invisible to X-Ray imaging and thus the navigation of the catheter in the vessel is a delicate and potentially dangerous process.

We suggest one methodology to help the re-canalization: guide the interventionist by means of a proper visualization of coronary arteries from CTA volumes. This is because the occluded artery is visible in the CTA, so that, with an appropriate registration, the cardiologist can actually see the invisible part of the artery by fusing data coming from the pre-operative CTA. Nonetheless, this possibility poses a series of severe and challenging problems: (i) The X-Ray images present a very low signal to noise ratio; (ii) the exact identification of the artery boundaries in angiography sequences, even by an expert medical doctor, could be difficult; (iii) the presence of an heterogeneous background, like spine, diaphragm, bones, stents, catheter guide, etc., makes difficult the automatic segmentation of arteries in X-Ray images; (iv) regarding the multi-modal registration, the CTA volumes do not contain elements that appears in the X-Ray images, thus the registration is actually between two different "objects"; (v) images captured in the two different modalities may represent the coronary tree in different phases of the cardiac cycle and, normally, present an important non-rigid deformation, that is different in both modalities. Considering all of these problems, it is necessary to *segment the arteries* both in the X-Ray and CTA volumes automatically, prior to their *non-rigid registration*. Some recent attempts considered only rigid XRay to CT affine registration, with partial while encouraging results [6, 8].

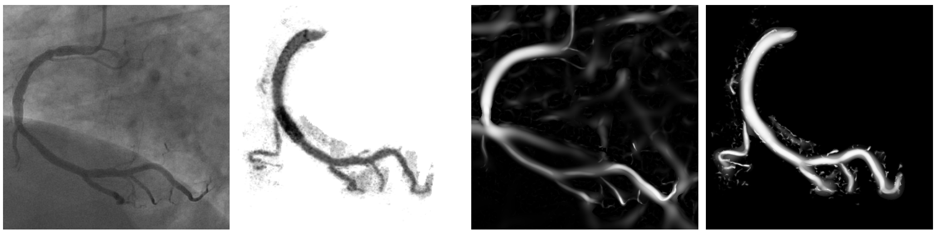
In this paper we show that some form of vessel detection/segmentation is required to obtain a good non-rigid registration between X-Ray and CTA images. Moreover, we propose the use of the SIFTflow [5], a methodology that is typically used for natural images, in the medical image context. The motivation to use SIFTflow for this specific problem, comes from the fact that it provides the required abstraction by describing the image locally using the SIFT descriptor and performing the registration in a way designed for "same class of objects" and not for the exact same object instance. In order to evaluate the approach, the performance of SIFTflow is compared with the well-known Free Form Deformation (FFD) [7], which is currently the state-of-the-art method in medical image registration. The use of SIFTflow in a specific area of medical imaging has been recently introduced in [2], while its use for multimodal registration is, at the best of our knowledge, totally novel. FFD has been successfully used for non-rigid registration purposes, so that it is a good base-line approach for the problem we are facing in this paper. Moreover, it can handle non iso-volumetric transformations, so it fits well with the case of multimodal artery non-rigid registration. In this paper we do not present a comparison to diffeo-morphic methods, since we do not need an invertible transformation; moreover the computational cost of diffeo-morphic methods is significantly higher than FFD and SIFTflow.

The long-term goal of our project is to provide a virtual visualization of the obstructed segment by means of fusing data coming from pre-operative CT and intra-operative X-Ray sequences. The results depicted in this paper provided an experimental proof of the potential of SIFTflow with proper pre-processing as a basic foundation of more sophisticated future methods.

2 Method

The proposed method is based on the proper combination of (i) a vessel segmentation/enhancement algorithm together with (ii) a method for multi-modal non-rigid registration.

To extract the coronary artery in CTA we use the method proposed in [9], as it has been proven to be competitive with other state-of-the-art methods and it is fully automatic. In our experiments, the method performed sufficiently well on low quality CTAs. Using the primary (CRA/CAU) and secondary (LAO/RAO) angles of the angiographic C-ARM, we use the segmented coronary artery to obtain a simulated 2D image, by projecting the 3D data following the C-ARM geometry, as extensively described in [3]. To enhance vessels in X-Ray images, we used the well-known Vesselness method [4]. Figure 1 shows an X-Ray image (a), a simulated X-Ray image using the segmented 3D CTA coronary artery (b), and the respective Vesselness maps (c-d). It is interesting to note that the Vesselness



(a) (b) (c) (d)

Fig. 1. An X-Ray image (a), a simulated X-Ray image using the segmented 3D CTA coronary artery (b), and the respective Vesselness maps (c-d).

method removes undesired background structures, as the spine bone and non-tubular annoying structures, as well as low spatial frequencies intensity changes. Nonetheless, Vesselness enhances also the catheter, that is in fact a tubular-like structure, and the diaphragm border. These two objects are not visible in the CTO projection, so that they can negatively affect the registration process.

2.1 Registration methods

In this paper we propose the use of SIFTflow for artery multi-modal registration and compare it to the well known FFD algorithm. To unify the description of both methods, we'll use the following notation. Being $\Phi \subset \mathbb{N}^2$ the lattice support of the image, let define $\boldsymbol{p}^{(M)} \in \Phi$ a generic point of the moving image M, and $\boldsymbol{w}(\boldsymbol{p}^{(M)}) \in \mathbb{R}^2$ as the displacement vector estimated by a non-rigid registration algorithm, that maps the point $\boldsymbol{p}^{(M)}$ to the corresponding point on the static image S, $\boldsymbol{p}^{(S)} = \boldsymbol{p}^{(M)} + \boldsymbol{w}(\boldsymbol{p}^{(M)})$. For the sake of compactness, in the remaining part of the paper we will use $\boldsymbol{w}(\boldsymbol{p}) \triangleq \boldsymbol{w}(\boldsymbol{p}^{(M)})$ considering in an implicit way that the displacement is defined only from the moving M to the static S image. The displacement vector can also be seen in terms of its two orthogonal components as $\boldsymbol{w}(\boldsymbol{p}) = (u(\boldsymbol{p}), v(\boldsymbol{p}))$. With $\boldsymbol{w}$ we denote the non-rigid transformation field, $\forall \boldsymbol{p}$; the symbol $\varepsilon(\boldsymbol{p}) \subset \Phi$ indicates a region centered in a generic point $\boldsymbol{p}$.

Free Form Deformation: Free Form Deformation [7] (FFD) is a non-rigid registration methodology that deforms the moving image M in order to match the static image S, modeling the non-rigid transformation field $\boldsymbol{w}$ using splines. A regular grid of splines is defined and eq. (1) is minimized over the splines parameters, using the Normalized Mutual Information (NMI) as a similarity measure between images.

$$\mathcal{C}(\boldsymbol{w}) = -\mathrm{NMI}(S(\boldsymbol{p}), M(\boldsymbol{p}+\boldsymbol{w}(\boldsymbol{p}))) + \lambda \sum_{\boldsymbol{p}} \left(\frac{\partial^2 \boldsymbol{w}(\boldsymbol{p})}{\partial x^2}\right)^2 + \left(\frac{\partial^2 \boldsymbol{w}(\boldsymbol{p})}{\partial y^2}\right)^2 \quad (1)$$

The grid is then iteratively refined to allow more local deformations. Eq (1) is composed of two terms: the former evaluates the goodness of the deformation by computing the NMI between the static and deformed moving image; the latter is a smoothness term that forces the second order derivative of the displacement field $\boldsymbol{w}$ to be small. The parameter λ provides a way to balance the contribution of both terms.

SIFTflow: SIFTflow has been introduced first in [5] as a method to register images that represent different instances of the same object class (*i.e.* cars), rather than different images of the same object. This has been obtained by using a dense SIFT descriptor to characterize every image point $\boldsymbol{p}$, denoted with $s(\boldsymbol{p})$. The non-rigid registration process is driven by the minimization of the following equation:

$$\begin{aligned} E(\boldsymbol{w}) = \sum_{\boldsymbol{p}} \|s_S(\boldsymbol{p}) - s_M(\boldsymbol{p}+\boldsymbol{w})\| + \frac{1}{\sigma^2}\sum_{\boldsymbol{p}} \left(u^2(\boldsymbol{p}) + v^2(\boldsymbol{p})\right) + \\ \sum_{(\boldsymbol{p},\boldsymbol{q})\in\varepsilon} \min\left(\alpha|u(\boldsymbol{p}) - u(\boldsymbol{q})|, d\right) + \min\left(\alpha|v(\boldsymbol{p}) - v(\boldsymbol{q})|, d\right). \end{aligned} \quad (2)$$

The first term accounts for the dissimilarity in terms of SIFT descriptor. Since the definition of $\boldsymbol{w}$ is not regularized, and the space search regions is large (40×40 pixels), the second term provides a first order regularization on $\boldsymbol{w}$; finally, the last term promotes the smoothness of $\boldsymbol{w}$. Parameters σ, α and d are used to provide the desired balance between the terms.

3 Experimental section

3.1 Material

To evaluate the proposed method, we used a set of 6 angiographic images from 4 patients. Images of Right Coronary Artery (RCA) have been acquired with a Philips Xcelera equipment, with pixel size of 0.33×0.33 mm. Regarding the CTA data, a set of 4 volumes has been acquired using a Toshiba Aquilion, with voxel size of $0.43\times0.43\times0.5$ mm. The coronary tree has been automatically segmented using the algorithm in [9], and then the RCA has been manually isolated from the aorta and other arteries. Finally, we collected only RCA images since the CTO is a pathology that mainly affects the RCA [1]. It is worth to note that the actual image resolution is higher since the image on the intensifier is a zoomed version of the coronary tree, due to the perspective effect. To provide measures of the actual vessels, the XRay image resolution has been estimated by relating the physical size of the catheter (a *6 French* in all experiments) to its size in millimeters. This resulted in an actual resolution of 0.237×0.237 mm. From here on, all the measures in millimeters refer to real-world dimensions using the proportion of 0.237 mm per pixels.

3.2 Algorithms setting

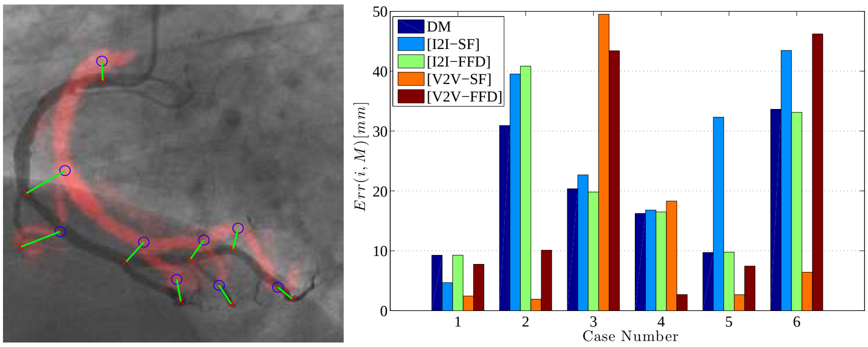
We are using three algorithms: a vessel enhancement method (Vesselness), FFD and SF. Regarding Vesselness, we set the scales in octaves, *i.e.* $s = 2^S$, for $S = \{1, 2, 3, 4\}$; this allows to highlight vessels with a caliber from 0.47 to a maximum of 7.58 mm. The parameters that weights the "tube-likeness" and the second order "structureness" have been set respectively to $\beta = 0.75$ and $c = 0.33$. The FFD has two main parameters, the λ (see eq. (1)) and the initial grid. In the experiments of this paper, we set $\lambda = 0$ and initial grid spacing of 128×128. This parametrization allows the FFD to handle the big deformations present in the images, and still provides a sufficient smoothing due to the use of splines. SIFTflow has different parameters that controls the smoothness of the solution and the magnitude of the displacements. In this paper we set $\alpha = 2$, $\sigma = 14$ and $d = 40$. This parametrization has been experimental derived starting from the standard settings in [5].

3.3 Results

To evaluate the automatic non-rigid registration, we collected the ground truth transformation by manually setting the correspondence between CTA and XRay images, as depicted in Fig. 2 (a). Due to the complexity of the images, a reliable ground truth can be obtained only by correspondences of clear landmarks as bifurcations, starting and ending points, and high curvature locations. For a given image i, we collected a number L of landmarks l, which ground truth translation is defined as $\boldsymbol{w}^{(i)}(l)$.

In our experiments, we performed the registration using four different pipelines: (1) FFD is applied on the images without any pre-processing (named [I2I-FFD]) and (2) with the Vesselness method (named [V2V-FFD]); (3) SF is applied on images without any pre-processing (named [I2I-SF]) and (4) with the Vesselness method (named [V2V-SF]). For all the cases, and for each method M, the displacement field is compared to the manually annotated landmarks translation as follows:

$$Err(i, M) = \frac{1}{L} \sum_{l} \|\boldsymbol{w}^{(i)}(l) - \boldsymbol{w}_M^{(i)}(l)\|.$$



(a) (b)

Fig. 2. (a) Ground-truth manually-annotated landmark registration pairs and (b) The registration error $Err(i, M)$ for all cases and methods.

The resulting average registration error is to be considered an upper bound of the actual error if considering the whole vessel instead of few landmarks. Figure 2(b) summarizes the results of the 6 cases we analyzed. The "DM" bars represent the average magnitude of the displacement between annotated landmark in XRA and CTA images; the rest of bars represent the average registration error of all the compared methods. As a general trend, the direct [I2I-FFD] registration is totally ineffective, despite the FFD can handle different modalities due to the use of the Mutual Information; nonetheless the background in XRA images does not allow FFD to find an acceptable solution, even at large grid spacings. The direct [I2I-SF] registration fails to converge to an optimal solution, and performs well in only one case (number 1); in some cases SF is prone to produce non-realistic results that totally disrupt the image content (see e.g. case # 5). When using vesselness as a pre-processing step, FFD improves its performance, getting the best result for case # 4 and slightly improving for case # 5. The [V2V-SF] method presents the best performance, being the best on 4 cases over 6.

Figure 3 show all the results of the experiment; the red overlay represents the artery obtained from the CTA projection. The first column shows the XRA and CTA without any registration. Cases # 3 and 6 present very challenging examples: in case # 3 the deformation of the artery in the XRA is so important that the two images represent two very different vessel morphologies. In case # 6 the CTA artery does not present a branch, that is visible in the XRA image; moreover the artery has few bifurcations, so that there is poor structure to help the registration.

4 Conclusion

In this paper we have shown preliminary results on non-rigid registration of coronary artery between X-Ray and CTA modalities. As expected, the image-to-image registration is a difficult task even for a mutual information-based algorithm, and a pre-processing step is necessary. In this paper we investigated the

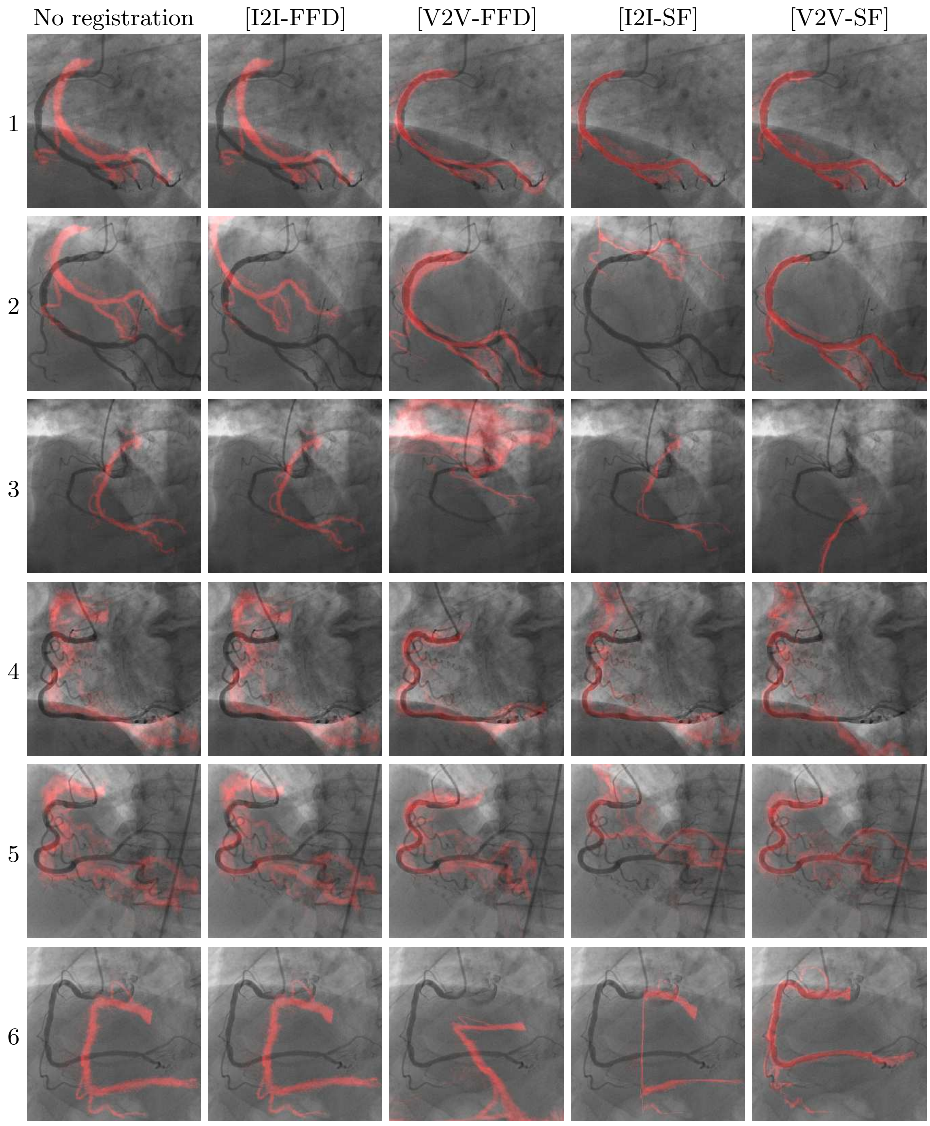


Fig. 3. Results of non-rigid registration with different pre-processing methods. The over-imposed red artery is the 2D CTA projection deformed according to the mentioned method.

use of the well known Vesselness method, with encouraging results; nonetheless, a higher level of abstraction should be necessary to remove background annoying objects. In some sense, SIFTflow provides the required abstraction by describing the image locally using the SIFT descriptor and performing the registration in a way designed for “same class of objects” and not for the exact same object instance. The analysis proposed in this paper does not want to be exhaustive and serves as a proof of concept for future research in segmentation and non-rigid registration of multi-modal cardiac imaging. Future works will be devoted in further regularization of the SIFTflow result, using a-priori knowledge of arterial motion; extend the SIFTflow functional to be able to handle partial occlusions, thus dealing with the CTO problem, and compare with other state-of-the-art registration algorithms.

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