MYOCARDIAL SEGMENTATION IN LATE-ENHANCEMENT MR IMAGES VIA REGISTRATION AND PROPAGATION OF CINE CONTOURS

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ABSTRACT

Segmentation of myocardium in Late Gadolinium Enhanced (LGE) MR images is often difficult due to accumulation of contrast agent in the infarct areas, leading to poor delineation from adjacent blood pools. Thus, manual determination of the endo- and epicardial contours is challenging, time consuming, and subject to significant intra- and inter-observer variability. In this paper, we propose to use prior information from cine images of the same patient to achieve accurate segmentation in the corresponding LGE images. The proposed method first delineates the endo- and epicardial borders in the higher quality cine images of the patient's heart. Then, a robust multiscale registration framework incorporating multiscale total variation (TV) flow as a preprocessing procedure is used to align the 3D cine and 2D LGE data for the same patient. The contours from the cine images are then propagated to the LGE dataset using the same transformation. Promising results were achieved through experimental validation.

***Index Terms*—** Cardiovascular MRI, image registration, image segmentation, multiscale total variation flow

1. INTRODUCTION

Viability assessment for a patient who has experienced prior myocardial infarction is essential for treatment planning. In particular, the location and size of the infarct inside the myocardium are important factors for determining the feasibility and value of revascularization procedures. Typically, two imaging datasets are acquired for viability assessment. First, a cine cardiac magnetic resonance (CMR) imaging acquisition is used to obtain a stack (10-15 slices) of images for evaluating the wall motion of the left ventricle (LV). Then, a gadolinium based contrast agent is injected into the patient, and a late gadolinium enhancement (LGE) MR scan is performed after a waiting period of approximately 15-20 minutes. The contrast agent will tend to accumulate in the infarct region due to the increased extracellular volume as a result of collagen fibres in the infarcted tissue replacing healthy myocytes. This will cause hyper-enhancement of the infarct region in the LGE images.

To locate and quantify the infarct tissue, a contouring step is required to delineate both the endocardial and epicardial borders of the myocardium in LGE images. The current clinical practice of manually contouring the LGE images is tedious, time consuming, and subject to significant intra- and inter-observer variability. However, automatic segmentation of the myocardial contours in LGE images is extremely challenging due to intensity inhomogeneity in the myocardium caused by the accumulation of contrast agent. Thus, most of the existing techniques use prior information from segmented cine CMR images to constrain the segmentation in LGE images [1, 2]. This approach is chosen because intensity values corresponding to the myocardium are relatively homogeneous in cine images and the intensity distributions between myocardium and the nearby blood pool have minimal overlap. Therefore, robust techniques exist for automatic segmentation of cine CMR images [3, 4]. In theory, the segmented contours from cine images can be directly transferred to the LGE images, as the patients are asked to lie still between the cine and LGE scans. However, in practice mis-alignments occur due to inadvertent patient movement, and respiratory motion. Therefore, when the contours from cine images are used as prior information, an accurate registration method is required to propagate the contours onto the LGE dataset.

In this paper, we propose a multiscale framework for registering the 3D cine volume to each of the 2D LGE slices, leading to automatic propagation of 3D cine contours onto the LGE images. We believe a 3D approach can be more accurate than a 2D framework as presented in [1], because corrections to potential through-plane motion can also be applied. In particular, both datasets are decomposed through a multiscale total variation (TV) flow [5, 6] scheme that yields different representations of the given images. Then, the images are iteratively registered in a coarse-to-fine manner. Finally, the contours obtained from the cine dataset are propagated, using

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the previous registration transform, to the LGE dataset.

2. METHODS

The proposed segmentation method combines several techniques to find the myocardial contours in the LGE dataset. The first step requires accurate delineation of myocardial contours in the cine image sequence. This can either be performed manually by an expert, which is less challenging compared to direct contouring of LGE images, or automatically using algorithms in [3, 4]. Next, multiscale TV flow is applied to both the cine and LGE datasets to decompose the images into coarse and fine scale features, which are then iteratively registered. Subsequently, the obtained registration parameters are used to transfer the cine contours onto the LGE dataset. The block diagram of this framework is illustrated in Fig. 1.

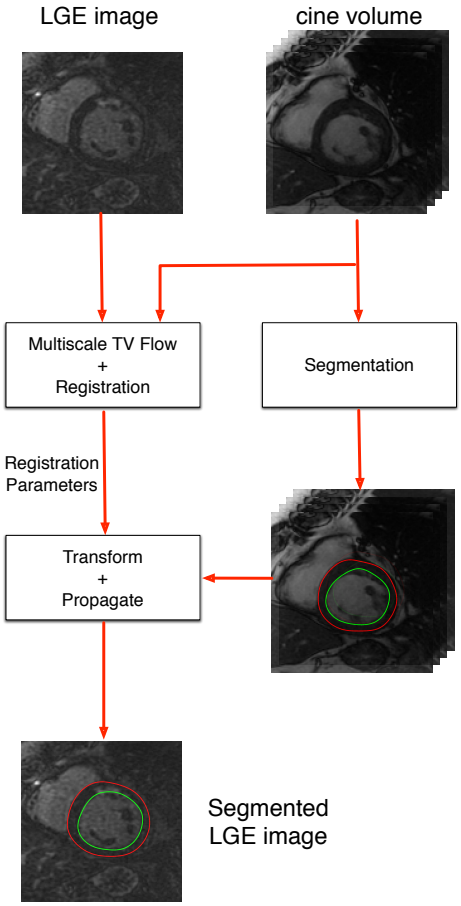

Fig. 1. Contouring workflow for LGE images using prior information from the corresponding cine volume.

2.1. Preprocessing using multiscale TV flow

Multiscale decomposition can be used to represent anatomical structures of varying scales, which are inherent in medical images. This is useful for registration techniques, which can focus on initially aligning large scale structures in two different datasets, while ignoring small scale features. This would provide a good initial guess of the registration parameters for subsequent registrations, where finer features are iteratively added in a coarse-to-fine manner.

In this paper, decomposition of an image f can be perceived as generating a smooth component u and a residual component $v = f - u$. Furthermore, the multiscale decomposition algorithms can generate a multiscale family $\{u_\lambda, v_\lambda\}$ where λ denotes an algorithm specific scale parameter. An example of a variational method for image decomposition [7] involves finding a solution u_λ that minimizes the following energy term:

$$E(u, f) := \frac{1}{\lambda}\int_\Omega |\nabla u| + \int_\Omega |f - u|^2, \qquad (1)$$

where $\Omega \subset \mathbb{R}^2$ denotes the imaging domain, and a smoothed version of f is represented by u_λ with scale $\sim 1/\lambda$. The choice of scaling parameter λ determines the amount of smoothing that is applied to the original image f. In the multiscale decomposition framework, f is first decomposed into $f = u_{\lambda_0} + v_{\lambda_0}$. Then, we decompose $u_{\lambda_0} = u_{\lambda_1} + v_{\lambda_1}$, with $\lambda_1 < \lambda_0$. This process is repeated iteratively to get successively smoothed versions $u_{\lambda_{i+1}}$ with coarser scale features according to $u_{\lambda_i} = u_{\lambda_{i+1}} + v_{\lambda_{i+1}}$. Thus, the following nonlinear multiscale decomposition is produced:

$$u_{\lambda_N} = f - \sum_{i=0}^{N} v_{\lambda_i} = f + \sum_{i=0}^{N} \frac{1}{2\lambda_i} \operatorname{div}\left(\frac{\nabla u_{\lambda_i}}{|\nabla u_{\lambda_i}|}\right). \qquad (2)$$

The divergence term in (2) formally comes from the Euler-Lagrange differential equation [8] of (1). This multiscale representation leads to the following integro-differential equation:

$$u(x,t) = f(x) + \int_0^t \frac{1}{2\lambda(s)} \operatorname{div}\left(\frac{\nabla u(x,s)}{|\nabla u(x,s)|}\right) ds, \qquad (3)$$

where $\lambda(t)$ is a real-valued, monotone decreasing function. That is, as time t increases, smoothing also increases. Differentiating (3) with respect to t yields:

$$\frac{\partial u}{\partial t} = \mu(t) \operatorname{div}\left(\frac{\nabla u}{|\nabla u|}\right), \qquad (4)$$

where we set the initial condition $u(x, t = 0) := f$ with the Neumann boundary condition, and $\mu(t) = 1/2\lambda(t)$ is the speed function, which is emperically set to $\mu(t) = 10^{1+2t}$. We consider equation (4) as multiscale TV flow, which is closely related to total variation flow [6]. The multiscale TV flow is used to decompose the cine and LGE datasets into their respective multiscale representations with successively larger scale structures. An example is shown in Fig. 2, where multiscale TV flow is applied to a single slice cine image.

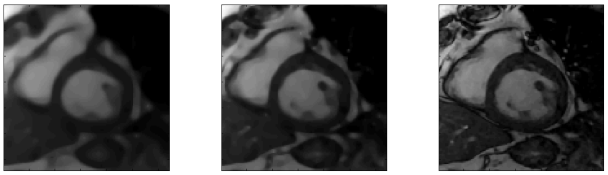

Fig. 2. Multiscale TV flow preprocessing: (a) - (c) show a cine image that has been decomposed using multiscale TV flow. Total amount of smoothing decreases from left to right, leading to coarse-to-fine representations of the original image.

2.2. Multiscale registration

Direct overlay of the contours from the cine image sequence onto the LGE dataset is not accurate because of potential patient motion between the two scans. Therefore, a robust registration method is required to first align the cine dataset with the LGE dataset, before applying the same transform to propagate the cine contours.

The general image registration task can be posed as an optimization problem as follows:

$$\arg\min_{w} \left\{ \mathrm{Dist}(f[w], g) \right\} \tag{5}$$

where $w := \langle \theta_x, \theta_y, \theta_z, t_x, t_y, t_z \rangle$ represents the registration parameters consisting of rotations and translations in x, y, z respectively; $f[w]$ and g represent the transformed cine volume and the reference LGE slice respectively. A rigid transform is used to align the two datasets, because both acquisitions are ECG gated to the same cardiac phase. The distance measure (Dist) between the two images is chosen to be mutual information (MI) [9] and the optimizer used is the simplex method [10].

Furthermore, the registration process is performed in a multiscale framework as illustrated in Fig. 3. The images f, g, and the initial guess of the registration parameters w_0 are inputs to the registration framework. Next, coarse scale features are extracted from the the original images f and g using multiscale TV flow, equation (4), to produce $u^f(\cdot, t_N)$ and $u^g(\cdot, t_N)$ for a large value t_N. These images are further down-sampled, represented by the operator D in Fig. 3, and subsequently registered using equation (5) to produce optimal registration parameters w_1 for the current scale. The latter acts as an initial guess for registration of finer scale feature images $u^f(\cdot, t_{N-1})$ and $u^g(\cdot, t_{N-1})$, where $t_{N-1} < t_N$. This process is iteratively repeated, where the optimal transformation w_{i+1} is used as the initial guess for the next finer scale registration until w_{final} is obtained at the finest level.

The multiscale registration approach is adopted because the optimization cost function is not strictly convex, leading to the presence of local minima. Thus, the optimizer may become trapped in one of these local minima, which is not the desired global solution. A multiscale scheme is more robust to local minima because initial registration only focuses on coarse scale features. This is equivalent to optimizing over a smoothed version of the cost function, such that the optimizer can converge to near vicinity of the desired solution. However, the iterative addition of finer scale features allows the algorithm to fine-tune the registration parameters until convergence is established at the optimal solution. Furthermore, the multiscale framework can reduce total registration time, since the input images are down-sampled at coarse scales. Improvements in accuracy and speed due to the use of a multiscale framework were described in a previous study [11].

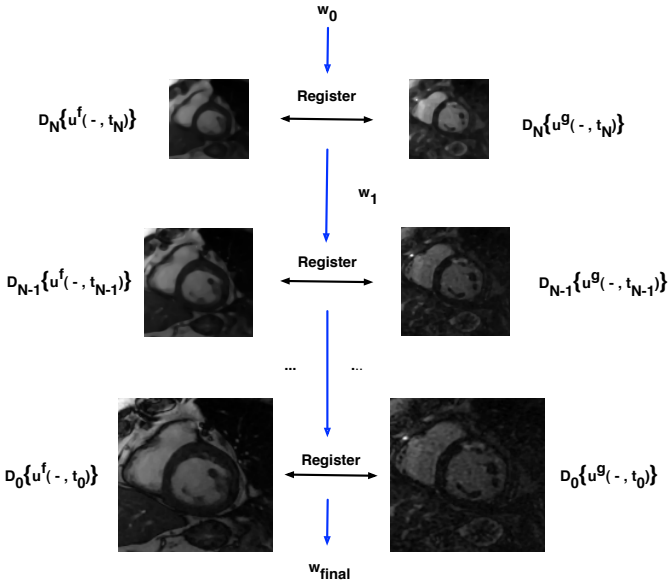

Fig. 3. Multiscale registration: registration is executed in a coarse-to-fine manner, where optimal registration parameters obtained at a coarse scale are used as initial guess at the next scale. This is repeated until optimal registration transform is obtained at the finest scale.

3. RESULTS

Quantitative evaluation of the proposed method was performed on data from 17 patients with previous myocardial infarctions. Each LGE dataset consists of a stack of 10-15 slices with imaging size of 256×256 and imaging resolution of 1.36×1.36 mm. The average perpendicular distance between the LGE contours obtained from the proposed method and the manually delineated contours by an expert were 1.92±0.87 mm and 1.65±0.73 mm for endo- and epicardial borders respectively. In contrast, a 2D-2D affine registration method without the use of the multiscale TV flow registration framework obtained errors of 2.75±1.32 mm and 2.69±1.28 mm for endo- and epicardial contours respectively. Lastly, direct overlay of cine contours onto the LGE

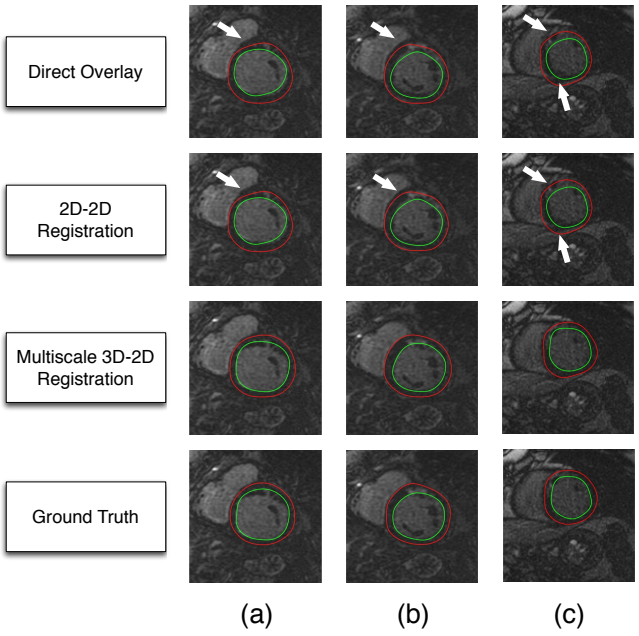

Fig. 4. Contour comparisons: different contour propagation method results are compared with the manually delineated contours by an expert (i.e. ground truth). This is illustrated for 3 different patient images (a)-(c). White arrows shows the inaccuracies in the contours as a result of the direct overlay and 2D-2D registration methods.

dataset without registration resulted in errors of 2.77 ± 1.72 mm and 2.76 ± 1.62 mm for endo- and epicardial contours respectively. Example results from the aforementioned contour propagation methods are illustrated in Fig. 4. The total registration time needed per dataset for the proposed multiscale method is approximately 30 s on a 2.66 GHz Intel Dual Core i7 Apple Macbook Pro with 4GB of memory.

4. CONCLUSIONS

In this paper, we presented a segmentation method for LGE images through the use of prior cine contours. The proposed method takes advantage of the fact that cine and LGE images are typically acquired within the same patient scan session approximately 15-20 minutes apart. Thus, the misalignment between the two datasets is relatively small due to inadvertent patient motion. Given myocardial contours from the cine images, our method accurately registers the 3D cine dataset to each individual 2D LGE imaging slice, and the same transformation is used to propagate the cine contours onto the LGE images. To ensure robustness and accuracy of the registration, a multiscale TV flow and multiscale registration framework is implemented to iteratively register the two datasets in a coarse-to-fine manner. Excellent results were shown through evaluation with real patient datasets.

5. REFERENCES

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