Joint Myocardial Registration and Segmentation of Cardiac BOLD MRI

Ilkay Oksuz[1,2], Rohan Dharmakumar[3], and Sotirios A. Tsaftaris[2]

[1]IMT Institute for Advanced Studies Lucca, [2]The University of Edinburgh,
[3]Biomedical Imaging Research Institute, Cedars-Sinai Medical, Los Angeles

Abstract. Registration and segmentation of anatomical structures are two well studied problems in medical imaging. Optimizing segmentation and registration jointly has been proven to improve results for both challenges. In this work, we propose a joint optimization scheme for registration and segmentation using dictionary learning based descriptors. Our joint registration and segmentation aims to solve an optimization function, which enables better performance for both of these ill-posed processes. We build two dictionaries for background and myocardium for square patches extracted from training images. Based on dictionary learning residuals and sparse representations defined on these pre-trained dictionaries, a Markov Random Field (MRF) based joint optimization scheme is built. The algorithm proceeds iteratively updating the dictionaries in an online fashion. The accuracy of the proposed method is illustrated on Cardiac Phase-resolved Blood Oxygen-Level-Dependent (CP-BOLD) MRI and standard cine Cardiac MRI data from MICCAI 2013 SATA Segmentation Challenge. The proposed joint segmentation and registration method achieve highers dice accuracy for myocardium segmentation compared to its variants.

Keywords: Segmentation, Registration, Markov Random Fields, Joint optimization, BOLD, CINE MR.

1 Introduction

Cardiac Phase-resolved Blood Oxygen-Level-Dependent (CP-BOLD MRI) is a new imaging technique, free of stress and contrast agents, used for the assessment of myocardial ischemia at rest [19]. The specific segmentation and registration among the cardiac phases in this cine type acquisition is crucial for automated analysis approaches of this technique, since it potentially leads to better specificity of ischemia detection [4]. To achieve this, precise segmentation and nonlinear registration of the myocardium among the frames (the cardiac phases) in the cine stack would be required. Unfortunately, at present due to BOLD contrast variations, classical approaches to segmentation [15] and registration [14] fail to reach sufficient accuracy.

In this paper, we propose a joint registration and segmentation scheme to generate accurate timeseries information for cardiac sequence. We adopt a joint optimization scheme [11] to optimize the registration term on sparse representations and segmentation terms for dictionary learning residuals. The motivation behind this choice is the mutual benefit of both functions, which can be directly translated to accurate registration and segmentation.

There are two major contributions of this work. First, we define a joint optimization scheme based on dictionary learning residuals and sparse representations for the first time. Second, we introduce an iterative dictionary update stage, which takes the spatial smoothness into account to increase discriminative power of the dictionary learning structure. With this, the dictionaries are ensured to be subject-specific and more robust for classifying the myocardium region.

The remainder of the paper is organized as follows: Section 2 investigates the prior art on joint registration and segmentation. Section 3 discusses the dictionary learning based methods for image registration and segmentation and presents the proposed joint optimization scheme for myocardial timeseries generation. The experimental results are described in Section 4 and, Section 5 concludes the paper.

2 Background

Registration and segmentation of organs in medical imaging are two major tasks, which are processed with two independent optimization schemes in most applications. One approach of solving both problems is using a sequential strategy to address both challenges, which results in concatenation of errors of both processes. Instead of a sequential segmentation and registration scheme, which uses estimated solution of one sub-problem as a prior knowledge to the other, joint optimization of two problems can be defined [21], where both problems are solved simultaneously. Early works merged the two processes with partial differential equations [20] and and in particular within level-set formulations [22]. More recent literature relies on joint optimization with single function simultaneously using Markov Random Fields (MRF)s [7]. MRFs are suitable for discrete labeling problems and the labels are defined as segmentation classes and discrete displacement vectors. The concept of utilizing mutual benefits between the registration and segmentation has been studied for the problem of atlas-based tumor segmentation for brain MRI [16]. Alchatzidis et al. [3] proposes to couple segmentation and registration scheme for classifying multiple regions in brain MRI and compared with standard post-registration label fusion strategies [2] . Mahapatra et al. [10] used a joint optimization scheme to detect the left ventricle (LV) in standard cine and perfusion MR images.

In joint registration and segmentation, the estimate of one set of parameters of registration should not adversely affect parameters of segmentation. An appropriate optimization scheme aims to balance these influences. Graph cuts is based on maximum-flow approach and is very effective in finding the global minimum or a strong local minimum of discrete MRF energy formulations [5]. However, a number of issues have to be addressed in using segmentation in-

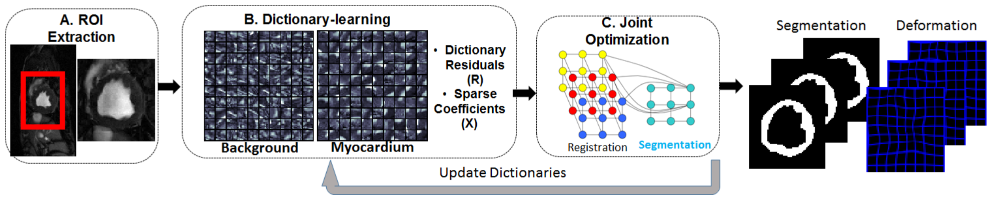

Fig. 1: Algorithm design for joint segmentation and registration. Region of interest extraction (Panel A). Dictionary learning from training images and calculation of residuals (R) and sparse coefficients(X) (Panel B). Multi-resolution deformation grids and exemplary connections with segmentation grid (Panel C)

formation for MRF-based registration. Registration and segmentation energies have to be combined such that there is no bias for a particular term. The mutual dependence of registration and segmentation has to be factored in the objective function.

In this work, we propose a joint optimization scheme for myocardial registration and segmentation to generate accurate deformations and segmentation masks for the entire cine stack. Our method builds upon the externally trained dictionaries of myocardium and background and uses priors on each problem jointly to extract and register the myocardial region. We introduce a dictionary update scheme to fuse subject-specific local information. Our algorithm generates deformations and segmentations for the entire cardiac sequence.

3 Methods

The details of our method are visualized in Figure 1. We extract a region of interest around LV blood pool using a similar preprocessing strategy to [17]. We use externally trained dictionaries of myocardium and background to define registration and segmentation terms for joint optimization. Then, these terms are optimized using a discrete graphical model over the labels of registration and segmentation. Finally, we update our dictionaries to enrich subject-specific information in the dictionaries and run the optimization process again.

3.1 Dictionary Learning based Image Segmentation

Dictionary learning based approaches have been used for segmentation of medical images [9]. In our specific algorithmic design, given some sequences of training images and corresponding ground truth labels, we can obtain two sets of matrices, Y^B and Y^M, where the matrix Y^B contains the background information and Y^M is the corresponding matrix referring to the myocardium. Squared patches are sampled around each pixel of the training images from both regions. The i-th column of the matrix Y^B (and similarly for the matrix Y^M) is obtained by concatenating the normalized patch vector of pixel intensities, taken around the i-th pixel in the background, along with the Gabor and HOG features of the same patch. The method detailed in [13] trains two dictionaries, D_k^B and D_k^M, and two sparse feature matrices, X_k^B and X_k^M using the K-SVD algorithm [1] for each class $C = \{B, M\}$:

$$\underset{D^C, X^C}{\text{minimize}} \|Y^C - D^C X^C\|_2^2, \text{ subject to } \|x_i^C\|_0 \leq \text{sparsity}$$

After the training given a new subject, a certain patch will be assigned to the class that gives the smallest dictionary approximation error using Orthogonal Matching Pursuit [18]. If $R_B = \|\hat{y}_i - D^B \hat{x}_i^B\|_2$ is less than $R_M = \|\hat{y}_i - D^M \hat{x}_i^M\|_2$, the patch is assigned to the background; otherwise, it is considered belonging to the myocardial region.

3.2 Graph-based Joint Optimization

In this section, we introduce our dictionary learning based joint optimization scheme for registration and segmentation of the myocardium. The general term for energy of a second-order MRF is defined as:

$$E(L) = \sum_{p \in \Omega} D_p(l_p) + \lambda \sum_{p,q \in N} V_{pq}(l_p, l_q)$$

where p and q denote the pixels, l_p and l_q denotes the registration and segmentation labels of the pixels p and q. λ controls the interaction between data term and smoothness term. The function is optimized over the labels $L = \{C, u\}$, which consists of the segmentation label C and discrete deformation u. We define the general data term $D_p(l_p)$ similar to [10]:

$$D_p(l_p) = D_{l_p}^1 + \gamma D_{l_p}^2$$

which consists of two terms, namely segmentation and registration data terms. Segmentation of the myocardium is defined over the dictionary learning residuals R_B and R_M. The penalty of the pixel p to be classified as myocardium is : $\kappa_M(p) = \frac{R_M(p)}{R_M(p)+R_B(p)}$. Similarly, the penalty for the same pixel to be classified as background is $\kappa_B(p) = \frac{R_B(p)}{R_M(p)+R_B(p)}$. Using these penalty definitions D_p^1 is defined as:

$$D_{l_p}^1 = \begin{cases} \sqrt{\kappa_M^r(p) * \kappa_M^f(p+u)}, & \text{if } C^r(p) = C^f(p+u) = M \\ \sqrt{\kappa_B^r(p) * \kappa_B^f(p+u)}, & \text{if } C^r(p) = C^f(p+u) = B \\ \sqrt{\kappa_B^r(p) * \kappa_B^f(p+u)} + \sqrt{\kappa_M^t(r) * \kappa_M^f(p+u)}, & \text{otherwise} \end{cases}$$

where $\kappa_M^f(p+u)$ corresponds to the penalty associated with myocardium class for the deformed floating image with displacement u. Similarly, $\kappa_B^r(p)$ corresponds to penalty of the reference image for the background class. This term ensures a low penalty for same labels of the displaced image and the reference image.

If the floating image and the reference image do favor different segmentation classes the penalty will be high.

The registration penalty term $D^2_{l_p}$ of the data term D_{l_p} is defined as:

$$D^2_{l_p} = \begin{cases} \| X^r_M(p) - X^f_M(p+u) \|_1, & \text{if } C^r(p) = C^f(p+u) = M \\ \| X^r_B(p) - X^f_B(p+u) \|_1, & \text{if } C^r(p) = C^f(p+u) = B \\ \| X^r_M(p) - X^f_M(p+u) \|_1 + \| X^r_B(p) - X^f_B(p+u) \|_1, & \text{otherwise} \end{cases}$$

where $X^r_M(p)$ corresponds to the sparse representation defined for D^M for the reference image and $X^f_M(p+u)$ defines sparse representation defined for the floating image at location $p+u$. This penalty is increased for dissimilar representation and also for the points with different segmentation labels.

Regularization term ensures the smoothness of segmentation labels and deformation field. The term favors the same segmentation labels in local neighborhoods and smooth deformations. The regularization term is defined as:

$$V_{pq}(l_p, l_q) = \begin{cases} 1, & \text{if } (C_p = C_q \text{ and } \| u_p - u_q \| \leq \varepsilon) \\ 1, & \text{if } (C_p \neq C_q \text{ and } \| u_p - u_q \| \leq \tau) \\ 100, & \text{otherwise} \end{cases}$$

where ε and τ restrict high displacements for local neighborhoods when segmentation labels agree or disagree respectively. To optimize the energy functional $E(L)$, we use graph cuts [5] on discrete labels of registration and segmentation.

3.3 Dictionary Update

We propose a dictionary update, which refines the dictionaries to inject subject-specific information. After every run of the MRF-based optimization scheme the estimated segmentation labels C are subject to change. We only extract patches that are corresponding to the points of label changes to update our dictionaries. We add square patches Y_u concatenated with Gabor and HOG features and train our dictionaries with Online Dictionary Learning (ODL) algorithm [12], which uses mini-batches to update the dictionaries. We add the new patches with changed labels for updating dictionaries we trained before. During the update the dictionary learning is initialized with the pre-trained dictionaries and this approach improves the discriminative power of the dictionaries in the next iteration.

4 Experimental Results

This section offers qualitative and quantitative comparison of our proposed method w.r.t. state-of-the-art methods, to demonstrate its effectiveness for myocardial segmentation and registration. Note that our method outperforms all supervised methods from current literature in both baseline and ischemia cases.

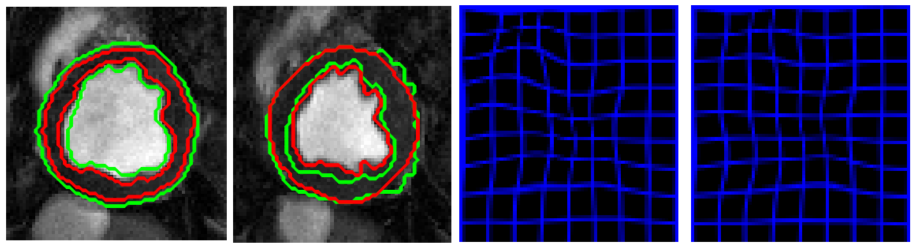

Fig. 2: Segmentation masks (red contours) and registration grid of proposed approach compared to CRS [11] (green contours) for an exemplary subject under baseline conditions in between end diastole and end systole frames.

4.1 Data Preparation and Implementation Details

2D short-axis images of the whole cardiac cycle were acquired at baseline and severe ischemia (inflicted as stenosis of the left-anterior descending coronary artery (LAD)) on a 1.5T Espree (Siemens Healthcare) in the same 10 canines along mid ventricle using both standard CINE and a flow and motion compensated CP-BOLD acquisition within few minutes of each other. The image resolution is 192×114 and each cardiac cycle has 25 frames approximately. We have utilized a strict leave one out cross validation experiment, where the patch size is defined as 11×11, dictionary size as 100 and sparsity threshold as 8. The parameters of deformation $\varepsilon = \sqrt{2}$ and $\tau = 3$ are optimized to ensure smooth labels for deformations. $\gamma = 0.7$ gave the optimal contribution of the data terms and $\lambda = 0.9$ ensures the balance of regularization and data terms. We have utilized three scales from coarse to fine for registration. The influence of the control points on each pixel is calculated using cubic B-Splines [8]. The displacement ranges from 2 to 6 pixels.

4.2 Visual Evaluation

We demonstrate a set of contours and a deformation grid to highlight the performance of our joint optimization and registration framework. In Fig. 2, we visualize the deformation grid in between the end systole and end diastole for an exemplary subject under baseline condition. We also illustrate the segmentation and deformation results of CRS [11] compared with our algorithm. Our method generates smooth deformation fields and smooth contours compared to CRS [11].

4.3 Quantitative Comparison

Table 1 summarizes our results for Dice overlap measure for myocardium. We compare our algorithm with an atlas-based segmentation technique, which relies on discrete registration performance using mutual information as a similarity metric [8]. Moreover, we include a recent joint registration and segmentation

Table 1: Dice overlap comparison of myocardial segmentation

	Baseline		Ischemia	
Methods	Standard Cine	CP-BOLD	Standard Cine	CP-BOLD
Atlas-based [8]	0.60 ∓ 0.03	0.54 ∓ 0.08	0.54 ∓ 0.08	0.45 ∓ 0.06
CRS [11]	0.71 ∓ 0.06	0.70 ∓ 0.06	0.69 ∓ 0.05	0.68 ∓ 0.07
Segmentation only	0.70 ∓ 0.05	0.71 ∓ 0.04	0.69 ∓ 0.04	0.68 ∓ 0.04
Sequential Seg. and Reg.	0.74 ∓ 0.06	0.72 ∓ 0.07	0.71 ∓ 0.07	0.68 ∓ 0.08
Proposed w.o update	0.75 ∓ 0.04	0.76 ∓ 0.04	0.75 ∓ 0.05	0.74 ∓ 0.04
Proposed	0.81 ∓ 0.04	0.80 ∓ 0.04	0.79 ∓ 0.04	0.80 ∓ 0.05

scheme CRS [11], which relies on sum of squared distances and edge-based differences as similarity term for registration. We generate results based on dictionary residuals for each pixel just for segmentation (Segmentation only). In addition, we used a sequential segmentation and registration (Sequential Seg. and Reg.), which first segments myocardium based on residuals and then refines the contours with propagation of the contours via registration based on sparse representations. Finally, we generate a variant of our algorithm, without using the dictionary update (Proposed w.o. update) to highlight the performance increase.

The proposed method outperforms all variants and other techniques in all four datasets. Segmentation information alone shows low performance compared to the variants, which incorporate registration. The sequential segmentation and registration has low performance compared to the proposed method. This low performance is due to the mutual dependence of registration and segmentation that has not been factored in the objective function, which is ensured with the proposed approach. Our method is superior to CRS [11], which relies on edge-based terms for myocardial registration. Ischemia condition generates a slight decrease in the performance for all methods. The proposed dictionary update enables a performance improvement thanks to less coherent dictionaries. The coherence of two dictionaries is calculated before and after the single dictionary update. The average coherence of two dictionaries 0.850 is reduced to 0.780 with the update. We illustrate an example set of dictionaries before and after the update in Fig. 3.

4.4 CAP Dataset

To demonstrate that our method works also non-BOLD, clinical data, we have tested our algorithm on cine cardiac training data set from the MICCAI 2013 SATA Segmentation Challenge. The dataset is part of the Cardiac Atlas Project (CAP) [6] and consists of 83 subjects with a varying in plane resolution from 0.7 mm to 2mm and a varying range of 19 to 30 frames per subject. On mid-ventricular level, we train our algorithm on 30 subjects to learn dictionaries for background and myocardium. Then, we test on the remaining 53 subjects and we achieve a dice score of 0.81 ∓ 0.04 compared to 0.80 ∓ 0.05 of CRS [11] algorithm

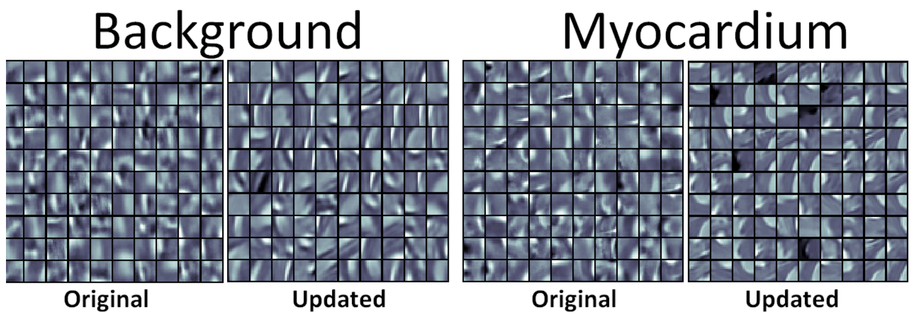

Fig. 3: Background and myocardium dictionaries before and after the dictionary update. Observe the increased number of unique myocardial patterns after the dictionary update.

(where standard deviation refers to variation among subjects and not on leave one cross validation).

5 Conclusion

In this paper, we propose a joint registration and segmentation scheme based on sparse representation. Our algorithm uses a MRF-based optimization scheme defined on dictionary learning residuals and at each iteration the dictionaries are updated using patches corresponding to the points that changed segmentation labels. This not only improves the performance by introducing subject specific information, but also adds more discriminative power as showcased with experiments. Currently, our algorithm works on 2D and we would like to extend our method to 3D. Moreover, currently we evaluate the deformation field visually and not quantitatively. One way to evaluate the registration performance is the target registration error, which will be available with the definition of landmark points for each frame. In the future, we would like to evaluate our approach on perfusion images that show stronger spatio-temporal variations.

References

1. Aharon et al., K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation, IEEE TSP, 54 (11): 4311-4322, 2006.
2. Alchatzidis et al., A discrete MRF framework for integrated multi-atlas registration and segmentation, IJCV, 121(1), 169-181, 2017.
3. Alchatzidis et al., Discrete Multi Atlas Segmentation using Agreement Constraints, BMVC, 2014.
4. Bevilacqua et al., Dictionary-Driven Ischemia Detection From Cardiac Phase-Resolved Myocardial BOLD MRI at Rest, IEEE TMI, 35(1): 282-293, 2016.
5. Boykov et al., Fast approximate energy minimization via graph cuts, IEEE PAMI, 23(11): 1222-1239, 2001.

6. Fonseca et al., The Cardiac Atlas Projectan imaging database for computational modeling and statistical atlases of the heart, Bioinformatics, 27(16): 2288-2295, 2011.
7. Gass et al., Simultaneous Segmentation and Multiresolution Nonrigid Atlas Registration, IEEE TIP, 23(7): 2931-2943, 2014.
8. Glocker et al., Dense image registration through MRFs and efficient linear programming, MedIA, 12(6): 731-741, 2008.
9. Huang et al., Contour tracking in echocardiographic sequences via sparse representation and dictionary learning, MedIA, 18: 253-271, 2014.
10. Mahapatra et al., Joint registration and segmentation of dynamic cardiac perfusion images using MRFs, MICCAI: 493-501, 2010.
11. Mahapatra et al., Integrating Segmentation Information for Improved MRF-Based Elastic Image Registration, IEEE TIP 20(1): 170-183, 2012.
12. Mairal, et al., Online dictionary learning for sparse coding, ICML: 689-696, 2009.
13. Mukhopadhyay, et al., Data-Driven Feature Learning for Myocardial Segmentation of CP-BOLD MRI, FIMH: 189-197, 2015.
14. Oksuz et al., Dictionary Learning Based Image Descriptor for Myocardial Registration of CP-BOLD MR, MICCAI: 205-213, 2015.
15. Oksuz et al., Unsupervised Myocardial Segmentation for Cardiac BOLD, IEEE TMI, 2017.
16. Parisot et al., Concurrent tumor segmentation and registration with uncertainty-based sparse non-uniform graphs, MedIA, 18(4): 647-659, 2014.
17. Queiros et al., Fast automatic myocardial segmentation in 4D cine CMR datasets, MedIA, 18(7): 1115-1131, 2014.
18. Tropp et al., Signal recovery from random measurements via orthogonal matching pursuit. IEEE Transactions on Information Theory, 53(12): 4655-4666, 2007.
19. Tsaftaris et al., Detecting Myocardial Ischemia at Rest With Cardiac PhaseResolved Blood Oxygen LevelDependent Cardiovascular Magnetic Resonance, Circulation: Cardiovascular Imaging, 6(2): 311-319, 2013.
20. Wang et al., Joint registration and segmentation of neuroanatomic structures from brain MRI, Academic Radiology, 13(9): 1031-1044, 2006.
21. Wyatt et al., MAP MRF joint segmentation and registration of medical images, MedIA, 7(4): 539-552, 2003.
22. Yezzi et al., A variational framework for integrating segmentation and registration through active contours, MedIA, 7(2): 171-185, 2003.