Unsupervised Myocardial Segmentation for Cardiac MRI

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Abstract. Though unsupervised segmentation was a de-facto standard for cardiac MRI segmentation early on, recently cardiac MRI segmentation literature has favored fully supervised techniques such as Dictionary Learning and Atlas-based techniques. But, the benefits of unsupervised techniques e.g., no need for large amount of training data and better potential of handling variability in anatomy and image contrast, is more evident with emerging cardiac MR modalities. For example, CP-BOLD is a new MRI technique that has been shown to detect ischemia without any contrast at stress but also at rest conditions. Although CP-BOLD looks similar to standard CINE, changes in myocardial intensity patterns and shape across cardiac phases, due to the heart's motion, BOLD effect and artifacts affect the underlying mechanisms of fully supervised segmentation techniques resulting in a significant drop in segmentation accuracy. In this paper, we present a fully unsupervised technique for segmenting myocardium from the background in both standard CINE MR and CP-BOLD MR. We combine appearance with motion information (obtained via Optical Flow) in a dictionary learning framework to sparsely represent important features in a low dimensional space and separate myocardium from background accordingly. Our fully automated method learns background-only models and one class classifier provides myocardial segmentation. The advantages of the proposed technique are demonstrated on a dataset containing CP-BOLD MR and standard CINE MR image sequences acquired in baseline and ischemic condition across 10 canine subjects, where our method outperforms state-of-the-art supervised segmentation techniques in CP-BOLD MR and performs at-par for standard CINE MR.

Keywords: Unsupervised Segmentation, Dictionary Learning, BOLD, CINE, MRI.

1 Introduction

Cardiovascular Disease (CVD) is the leading cause of mortality worldwide, and the modern analysis of cardiac function using imaging techniques (specifically

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Cardiac CINE MR) is an effective way of diagnosing CVD. An emerging cine-like cardiac modality is Cardiac Phase-resolved Blood Oxygen-Level-Dependent (CP-BOLD) MR, a truly noninvasive method that identifies the ischemic myocardium by examining changes in myocardial signal intensity patterns as a function of cardiac phase [19].

Fully supervised myocardial segmentation (i.e., separating myocardium from the rest of the anatomy) developed for standard CINE MR, however, underperform in the case of CP-BOLD MR due to the spatio-temporal intensity variations of the myocardial BOLD effect [14,19]. Thus, in addition to violating shape invariance (as with standard CINE MR), the principal assumption of appearance invariance (consistent intensity [12]) is violated in CP-BOLD MR as well. As a result, no automated CP-BOLD MR myocardial segmentation algorithms exist, and semi-automated methods based on tracking are currently employed [18]. We hypothesize that this is due to the lack of exploiting the unsupervised techniques in a sparse representation setting, which can be an effective tool for developing features that are invariant to temporal and inter-subject variabilities, yet unique and descriptive. In addition, we also argue that the temporal consistency assumption for myocardial segmentation of standard CINE MR is a special case of the more generalized spatio-temporal variability observed in CP-BOLD MR. Consequently, developing generalized features for CP-BOLD MR should also address the problems of myocardial segmentation of standard CINE MR.

In this paper, rather than relying on low-level features often used for representing the myocardium when developing segmentation methods for standard CINE MR, which are inconsistent for CP-BOLD MR, a fully unsupervised motion and sparse representation-based feature selection technique has been developed to accommodate the myocardial BOLD effect. The only assumption is that the myocardium moves differently than its surrounding background anatomy. This strategy is also motivated by the findings of [9] where sparse representation using dictionaries are shown to be invariant under intensity changes. In addition, the sparse representation is capable of retaining semantic information of the myocardium [21]. This essentially enables myocardial segmentation in cardiac MR image sequences (i.e. CINE stack) without any form of manual intervention e.g., landmark selection, ROI selection, spatio-temporal alignment to name a few. The unsupervised motion and sparse-representation strategy is designed to facilitate this key observation. Each frame is coarsely segmented (over-segmented) based on the optical flow vectors, inspired by [10]. The appearance and motion of the coarsely-segmented background is sparsely represented in a patch-based discriminative dictionary learning technique. A one-class Support Vector Machine (SVM) [15] is employed on the learnt sparse representation of all the pixels in the image sequence to classify myocardium from the background.

The main contributions of the paper are twofold. First of all, we revisit fully unsupervised myocardial segmentation technique employing no manual intervention and minimal myocardial motion-pattern assumption for solving general myocardium segmentation problem in standard and emerging cardiac MR imaging modalities. Secondly, we have employed a joint motion and sparse representation based technique, where the motion not only generates a rough estimate of the myocardium, but also guides the sparse representation stage to a smooth solution based on the motion of the myocardium.

The remainder of the paper is organized as follows: Section 2 discusses the related work, Section 3 presents the proposed method with results are described in Section 4. Finally, Section 5 offers discussion and conclusion.

2 Related Work

The automated myocardial segmentation for standard CINE MR is a well studied problem [12]. Most of these algorithms can be broadly classified into two categories based on whether the methodology is unsupervised or supervised one.

Unsupervised segmentation techniques with no or weak priors were employed early-on for myocardial segmentation of cardiac MR, almost all of which require minimal or advanced manual intervention [12]. Among the very few unsupervised techniques which are fully automated, most similar ones to our proposed method are those considering motion as a way to propagate an initial segmentation result to the whole cardiac cycle [5], [6] and [11]. Only Lynch et. al. [8] considered motion as an intrinsic entity in a temporal deformation model with level-sets for fully automatic unsupervised segmentation.

However, supervised segmentation techniques have received more attention in recent years and in particular, Atlas-based supervised segmentation techniques have achieved significant success [12]. The myocardial segmentation masks available from other subject(s) are generally propagated to unseen data in Atlas-based techniques [2] using non-rigid registration algorithms like diffeomorphic demons (dDemons) [20], FFD-MI [3], probabilistic label fusion or SVM [2]. Segmentation-only class of supervised techniques, on the other hand, mainly focuses on feature-based representation of the myocardium. Texture information is generally considered as an effective feature representation of the myocardium for standard CINE MR images [22]. Patch-based static discriminative dictionary learning technique (SJTAD) [16] and Multi-scale Appearance Dictionary Learning technique [4] have achieved high accuracy and are considered as state-of-the-art mechanisms for supervised myocardial segmentation. The hindsights of all the supervised methods are the requirements of lots of data for training and a robust feature matching framework, which is especially critical for emerging cardiac modalities such as CP-BOLD MR. In this paper, we follow a segmentation approach where the major feature includes using motion information and discriminative dictionary learning based sparse representation in a fully unsupervised fashion.

3 Method

Our proposed Unsupervised Motion and Sparsity based Segmentation (UMSS) method (as shown in Figure 1) for segmenting 2D Cardiac MR (both standard CINE and CP-BOLD) image sequences is described here in details.

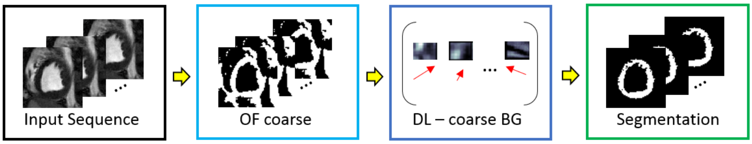

Fig. 1. Description of the proposed method. (see text for details)

Optical Flow Based Coarse Segmentation: Our first step is to compute optical flows between two subsequent frames (I_t, I_{t+d}) of the given image sequence using [7]. The motion boundary of the optical flow can be measured simply by calculating the gradient. We have computed the coarse segmentation by applying a threshold T_c on the gradient vectors as shown in Algorithm 1.

Dictionary Learning of Background: Given a sequence of images $\{I_t\}_{t=1}^{T}$ and corresponding coarse segmentation labels obtained from Optical Flow motion boundary as described earlier, we can obtain a matrix, $\{Y = [Y^{cB}Y^{cF}]\}$, where the matrix Y^{cB} and Y^{cF} contains the coarse background and Foreground information respectively. Information is collected from image and motion patches: squared patches centered around each pixel of the image and its corresponding motion matrix. More precisely, the p-th column of the matrix Y^{cB} is obtained by concatenating the normalized patch vector of pixel intensities and motion vectors taken around the p-th pixel in the coarse background. The Dictionary Learning part of our method takes as input this matrix Y^{cB}, to learn a dictionary D^{cB} and a sparse feature matrix X^{cB}. Dictionaries and sparse features are trained via the K-SVD algorithm [1]. We use the "Gram matrix" $(G^{cB} = (Y^{cB})^T Y^{cB})$ to promote diversity in the initialization step. The idea is to have a subset of patches as much diverse as possible to train dictionaries and sparse features. To ensure a proper discriminative initialization, patches that correspond to high values in the Gram matrix are discarded from the training before performing K-SVD. We sort the training patches w.r.t. the sum of their related coefficients in the Gram Matrix, and we prune them by choosing a certain percentage.

One-Class SVM for Segmentation: The goal of the segmentation problem is to assign to each pixel of the image sequence a label, i.e. establish if the pixel is included in the background or the myocardium. To perform this classification, we use the coarse Background dictionary $\{D^{cB}\}$ previously learnt with Discriminative Dictionary Learning technique for sparse representation of the appearance and motion features. We compute the sparse feature matrix $X = [X^{cB}X^{cF}]$ for all the pixels of the image sequence with OMP [17]. The classification is performed by constructing the classifier from only the sparse-features of coarse Background class X^{cB} (the p-th column of the matrix X^{cB}, x_p^{cB}, is considered as the discriminative feature vector for the particular pixel p) using a one-class SVM framework [15]. Supposing for each pixel p of coarse Background class, there is a high dimensional feature space F, then each sample is represented in F by $\Phi(x_{p\in cB})$ and the objective function is formulated as follows:

Algorithm 1. Unsupervised Motion and Sparsity based Segmentation (UMSS)

Input: Image sequence from single subject
Output: Predicted Myocardium masks across the sequence

Calculate Optical Flow $\overrightarrow{f}_p$ at each pixel p between pairs of frames (I_t, I_{t+d})
Measure motion boundary from gradient of Optical Flow $B_p = 1 - exp(-\lambda \left\| \nabla \overrightarrow{f}_p \right\|)$
    where λ is the parameter controlling steepness, $B_p \in [0, 1]$.
Compute Coarse segmentation $C_p \in \begin{smallmatrix} cB, if B_p < T_c \\ cF, if B_p \geq T_c \end{smallmatrix}$
Collect all $C_p \in cB$ and Calculate $Y_p^{cB} = [I_{p\pm\Delta}; \overrightarrow{f}_{p\pm\Delta}]$
Discard atoms with high values in intra-class Gram matrix G^{cB}
Learn dictionary and sparse feature matrix with the K-SVD algorithm

$$\underset{D^{cB}, X^{cB}}{\text{minimize}} \|Y^{cB} - D^{cB}X^{cB}\|_2^2 \quad \text{s. t.} \quad \|x_{p\in cB}\|_0 \leq L$$

Train one-class SVM on X^{cB} using Equation 1
Test on all sparse features $X \in x_{p\in(cF\cup cB)}$ for final classification

$$\underset{W\in F, \eta\in\mathbb{R}^l, b\in\mathbb{R}}{\text{minimize}} \frac{1}{2}W^T W + \frac{1}{\nu l}\sum\nolimits_{p\in cB} \eta - b \quad \text{s. t.} \quad W \cdot \Phi(x_{p\in cB}) \geq b - \eta, \eta \geq 0 \quad (1)$$

Here, W is the normal vector that represents the support, b is the threshold of function f, $\eta_{p\in cB}$ is the slack variable and ν is the parameter that represents the fraction of sample that should be accepted as the other class. During testing, sparse features for all the pixels of the image sequence, stored in matrix $\hat{X}$ are fed to the classifier learnt on the coarse Background features, to classify the myocardial region as the other class. In addition, a Hough transformation-based post processing step is employed by fitting parametric circles to enforce the shape constraint of the myocardium. Note that the later step is a rudimentary way of ensuring shape-based constraints. Treating it in a more sophisticated way, using probabilistic models (e.g. Graph-cut with coarse Background as a sink) or level-set, can potentially improve the performance.

4 Results

This section offers a qualitative analysis and quantitative comparison of our proposed UMSS method w.r.t. state-of-the-art methods, to demonstrate its effectiveness for myocardial segmentation. Note that our method outperforms all supervised methods from current literature in both baseline and ischemia cases of CP-BOLD MR, whereas yields state-of-the-art results for both baseline and ischemia cases of standard CINE MR.

Data Preparation and Parameter Settings: 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 the mid ventricle using both standard CINE and a flow and motion compensated CP-BOLD acquisition within few minutes of each other [19].

As for the parameters of UMSS, in this paper we have empirically chosen a d of 5 and a threshold T_c of 0.4 for coarse segmentation based on Optical Flow, 9×9 as the patch size, λ of 0.5, ν of 0.2 and a pruning of 10% for Gram Filtering. Each sparse feature has been represented by 5 non-zero elements whereas a dictionary of 10 atoms is chosen for coarse Background representation. We computed the myocardium segmentation across the whole stack of image sequences for each subject and tested the parameter sensitivity within a reasonable range, but the detailed performance chart is omitted for brevity.

Quantitative Comparison: As segmentation quality metric, the Dice coefficient, which measures the overlap between ground truth segmentation masks and those obtained by the algorithm(s), is employed. For our implementation of *Atlas-based segmentation methods*, the registration algorithms dDemons [20] and FFD-MI [3] are used to propagate the segmentation mask of end-diastole image from all other subjects to the end-diastole image of the test subject, followed by a majority voting to obtain the final myocardial segmentation. For *supervised classifier-based methods*, namely Appearance Classification using Random Forest (ACRF) and Texture-Appearance Classification using Random Forest (TACRF) random forests are used as classifiers to get segmentation labels from different features. To provide more context, we compare our approach with *dictionary-based methods*, SJTAD and RDDL. SJTAD is an implementation of the method in [16], whereas the discriminative dictionary learning of [13] is used for RDDL. Finally to showcase the strengths of our design choice of sparse representation using discriminative dictionary learning, we have considered two additional variants of UMSS, without Dictionary Learning (UMSS No DL) and without concatenating optical flow features with intensity for Dictionary Learning (UMSS No Motion). All quantitative analysis for supervised methods are performed using strict leave-one-subject-out cross validation.

As Table 1 shows, overall, for standard CINE, most algorithms perform adequately and the presence of ischemia slightly reduces performance. However, when BOLD contrast is present, other approaches fail to accommodate changes in appearance due to contrast, but UMSS obtains consistent performance. Specifically, Atlas-based methods are shown to perform well in standard CINE but poorly in CP-BOLD. ACRF and TACRF, instead, show very low performance in both cases. Among dictionary-based methods, SJTAD performs well in standard CINE MR, but under-performs in CP-BOLD MR. When comparing with its variants, UMSS shows that both Dictionary Learning and motion information are extremely beneficial.

Qualitative Analysis: The quality of myocardial segmentation by UMSS for both baseline and ischemia cases across standard CINE and CP-BOLD MR is shown in Figure 2. Note that UMSS results in very smooth endo- and epicardium contours which closely follow ground truth contours generated by the experts and can be attributed to the successful representation of myocardial motion.

Table 1. Dice coefficient (mean (std)) for segmentation accuracy in %.

	Baseline		Ischemia	
Methods	Standard CINE	CP-BOLD	Standard CINE	CP-BOLD
Atlas-based methods				
dDemons [20]	60(8)	55(8)	56(6)	49(7)
FFD-MI [3]	60(3)	54(8)	54(8)	45(6)
Supervised classifier-based methods				
ACRF	57(3)	25(2)	52(3)	21(2)
TACRF	65(2)	29(3)	59(1)	24(2)
Dictionary-based methods				
SJTAD [16]	71(2)	32(3)	66(3)	23(4)
RDDL [13]	42(15)	50(20)	48(13)	61(12)
Proposed Unsupervised method				
UMSS No DL	25(9)	26(12)	19(5)	18(7)
UMSS No Motion	49(15)	42(19)	51(14)	53(12)
UMSS	62(20)	71(10)	65(14)	66(11)

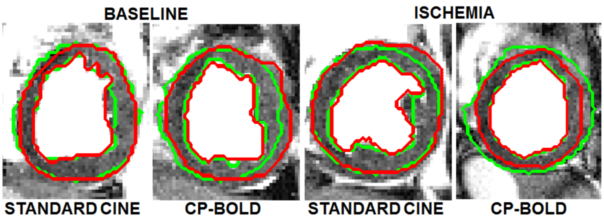

Fig. 2. Segmentation result (green) of UMSS for both CP-BOLD MR and standard CINE MR at baseline and ischemic condition superimposed with corresponding Manual Segmentation (red) contours delineated by experts.

5 Discussions and Conclusion

This study motivates us to rethink the standard assumptions regarding the segmentation of the myocardium in MR image sequences, especially to accommodate emerging cardiac MR imaging modalities. In particular, deviating from fully supervised techniques (the performance of which heavily depends on the amount of training data) towards unsupervised ones can benefit in multitude of ways: from operating on no training data, better handling of variability in image contrast to no manual intervention. In addition, this work has shown that unsupervised methods can still deliver state-of-the-art performance even for standard CINE MR. The proposed algorithm does not exploit the spatio-temporal information across cardiac phases and doing so by introducing graph-based formulation should increase performance in future extensions. UMSS can be an effective tool in challenging datasets where inter-acquisition variability prohibits the effectiveness of supervised segmentation strategies. Finally, such post-processing tools are expected to be instrumental in advancing the utility of emerging cardiac MR imaging techniques, e.g., CP-BOLD MR, towards clinical translation.

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