DATA DRIVEN FEATURE LEARNING FOR REPRESENTATION OF MYOCARDIAL BOLD MR IMAGES

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Introduction: Cardiac Phase-resolved Blood Oxygen-Level-Dependent (CP-BOLD) MR is a truly noninvasive (no contrast or stress agents, ionizing radiation and repeatable within the same exam) method determining the presence of ischemic heart disease[1]. CP-BOLD identifies the ischemic myocardium by examining changes in myocardial signal intensity patterns as a function of cardiac phase[1]. However, visualizing and quantifying such changes requires significant post-processing, including myocardial segmentation to isolate the myocardium. The spatio-temporal intensity changes in this acquisition challenge most automated myocardial segmentation algorithms (developed for standard CINE MR), since they violate the principal assumption of appearance invariance (consistent intensity). As a result, no automated myocardial segmentation algorithms exist, and semi-automated methods based on tracking are currently employed[2]. We hypothesize that it is due to the lack of appropriate features, which best represent appearance and texture in CP-BOLD images. Better features are necessary for the development of improved segmentation algorithms.

Purpose: In this work, we learn appropriate features using a multi-scale dictionary learning technique, which creates compact representations of appearance and texture for CP-BOLD MR.

Methods: Imaging Studies: 2D short-axis images 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 with parameters as described in[1]. Learning Features for Myocardial Segmentation: Appearance and shape invariance are the two main assumptions of general image segmentation strategies. Cardiac motion affects the shape invariance assumption, thus necessitating texture information as an effective feature representation of cardiac MR images[3]. The varying SSFP BOLD signal intensities, however violate the appearance invariance assumption as well, prompting to leverage Dictionary Learning techniques for finding better features for CP-BOLD myocardium representation. We adopt the well-known patch-based discriminative dictionary learning techniques[4,6] to learn from previously segmented data. Training commences by extracting around each pixel multiple square patches at different scales. We normalize each patch to unit norm (to impose appearance invariance), convert it into a column vector and append to it the multi-scale Gabor and HOG features to form a column vector Y. During training, two separate dictionaries of patches are learnt for myocardium and background using a discriminative initialization step (discarding atoms with high values in intra-class Gram matrix) followed by *K-SVD*[5] and a discriminative pruning (discarding atoms with high values in inter-class Gram matrix). This multiscale sparse representation is considered as the feature for that particular pixel. Statistical Analysis: To validate the accuracy of the proposed feature selection technique, we learn sparse dictionaries of augmented features of 9 canine subjects (each containing approximately 30 frames to represent one complete cardiac cycle) and test on the one left out in a strict leave-one-subject-out cross validation framework. To highlight the improvements these features introduce when segmenting the myocardium, we devise a rudimentary automated myocardial segmentation algorithm based on our learned features. Given an unseen image, we extract multiscale patches, obtain the feature vector, calculate the sparse representation using Orthogonal Matching Pursuit **(**OMP), and based on majority voting over all scales we retrieve the final classification for each pixel. To demonstrate the effects of BOLD contrast and ischemia we compare our approach with several patch-learning based segmentation algorithms starting from simple Appearance Classification using Random Forest (*ACRF*), joint Texture and Appearance Classification using Random Forest (*TACRF*) to sparse approximation on Static Joint Texture and Appearance Dictionary (*SJTAD*)[6]. We use the Dice coefficient, which measures the overlap between ground truth segmentation masks and those obtained by the algorithms as the segmentation quality metric. To ensure the significance of our proposed method, we have used a paired *t-test* between the results of our proposed method and each one of ACRF, TACRF and SJTAD.

Results: Table 1 shows the quantitative comparison of our proposed method with respect to the other techniques. Note that when standard cine acquisition is used, 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. For both baseline and ischemia cases of CP-BOLD MR, our method significantly outperforms the others in a paired t-test with (*, $p<0.001$), whereas similar paired t-test yield ($^{\#}$, $p<0.05$) and ($^{\$}$, $p<0.01$) for baseline and ischemia respectively in case of standard CINE MR. Fig. 1 illustrates a small exemplar set of discriminative patches learnt by our proposed method for myocardium and background of CP-BOLD MR images. It is evident from visual inspection that the learnt patches of myocardium are significantly different from those of the background which explains the performance boost of our proposed method.

Discussion: We show that the presence of BOLD contrast challenges current state-of-the-art approaches for myocardial segmentation based on patch-based representations of appearance. With the proposed multiscale discriminatory framework we have identified discernible appearance and texture patterns for CP-BOLD MR images. This suggests that we can successfully select important features that can be used towards better automated CP-BOLD MR segmentation algorithms. These features can be readily integrated in any framework that relies on obtaining pixel-level descriptions of the myocardium[7].

Conclusions: Rethinking the assumptions of most commonly employed analysis algorithms is critical for successfully developing the appropriate analytical tools necessary to meet the new challenges posed by myocardial CP-BOLD MR. By learning appropriate features to best represent texture and appearance in cardiac BOLD, in this study we show that it is possible to improve the performance of automated algorithms for myocardial CP-BOLD. Such post-processing tools are expected to be instrumental in advancing the utility of cardiac CP-BOLD MR towards effective clinical translation.

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

	Baseline		Ischemia	
Methods	**CINE**	**CP-BOLD**	**CINE**	**CP-BOLD**
ACRF	0.57±0.03	0.25±0.02	0.52±0.03	0.21±0.02
TACRF	0.65±0.02	0.29±0.03	0.59±0.01	0.24±0.02
SJTAD[6]	0.71±0.02	0.32±0.03	0.66±0.03	0.23±0.04
Proposed	**0.75±0.03$^{\#}$**	**0.75±0.02***	**0.72±0.02$^{\$}$**	**0.71±0.02***

Note: A paired t-test between the proposed method and SJTAD is performed in each case (same acquisition and condition): *, $p<0.001$; $^{\#}$, $p<0.05$ and $^{\$}$, $p<0.01$.

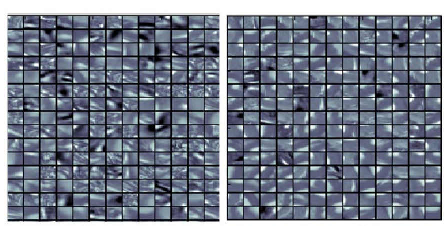

Fig. 1. Exemplar set of discriminative patches for Myocardium and Background are learnt by the proposed method on CP-BOLD MR images. It is important to note that the average value of non-diagonal elements of the final inter-class gram matrix is 0.24, which evidences that the learnt dictionaries are discriminative.

References: (1) Tsaftaris et al., *Circ Cardiovasc Img* 6(2):311-9 2013; (2) Tsaftaris et al., *ICIP,* 2980-3, 2008; (3) Zhen et al., *MICCAI*, 586-593, 2014; (4) Bai et al., *IEEE TMI* 32(7): 1302-15, 2013; (5) Aharon etal., *IEEE TSP* 54(11): 4311-22, 2006; (6) Huang et al., *MedIA* 18: 253-271, 2014; (7) Tavakoli et al., *MedIA* 117: 966-989, 2013.