Detection of Fibrosis in Late Gadolinium Enhancement Cardiac MRI using Kernel Dictionary Learning-based Clustering

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Abstract

In this paper we address the problem of fibrosis detection in patients with Hypertrophic cardiomyopathy (HCM) by using a sparse-based clustering approach and Dictionary learning. HCM, as a common cardiovascular disease, is characterized by the abnormal thickening, architectural disorganization and the presence of fibrosis in the left ventricular myocardium. Myocardial fibrosis in HCM leads to both systolic and diastolic dysfunction. It can be detected in Late Gadolinium Enhanced (LGE) cardiac magnetic resonance imaging. We present the use of a Dictionary Learning (DL)-based clustering technique for the detection of fibrosis in LGE-Short axis (SAX) images. The DL-based detection approach consists in two stages: the construction of one dictionary with samples from 2 clusters (LGE and Non-LGE regions) and the use of sparse coefficients of the input data obtained with a kernel-based DL approach to train a K-Nearest Neighbor (K-NN) classifier. The label of a test patch is obtained with its respective sparse coefficients obtained over the learned dictionary and using the trained K-NN classifier. The method has been applied on 11 patients with HCM providing good results.

1. Introduction

Hypertrophic cardiomyopathy (HCM) is the most common cardiovascular disease. It is mainly characterized by the abnormal thickening of the myocardium and the presence of fibrosis. HCM is a disease with variable prognosis [1]. A better characterization of HCM and fibrosis is still challenging in caridac imaging. Several studies have shown the relevance of Late Gadolinium Enhancement (LGE) in Cardiovascular Magnetic Resonance (CMR) imaging in the location and the assessment of myocardial scar and fibrosis [2]. The accurate estimation of the transmural extent of the hyper-enhanced regions is crucial for diagnosis and to estimate functional myocardial recovery after acute myocardial infarction and reperfusion therapy. An automated segmental scoring of infarct extent begins with the detection of the infarct on the images. Several methods based on the tunning of thresholds with user manual interaction [3–5] or automated definition of the infarcted zones using morphological operators [6] have been developed to this end. An overview of previously published scar tissue detection, quantification and segmentation methods is presented in [7] where a standardised evaluation benchmarking framework for algorithms segmenting fibrosis and scar in left atrium (LA) myocardium from LGE-CMR images is also presented. Some of the methods are based on clustering that avoid the choice of gray level thresholds. For example, the fuzzy c-means method [8] is an unsupervised approach providing each voxel with a level of membership to both, LGE and non-LGE classes, describing the belongingness of the voxel to the class. Segmentation of fibrosis or scar in LGE-CMR is challenging due to multiple causes including contrast variation due to inversion time, signal-to-noise ratio, motion blurring and artifacts.

In this paper, we present the use of a Dictionary Learning (DL)-based clustering technique for the detection of fibrosis in LGE-MRI following the idea of the framework for clustering datasets that are well represented in the sparse modeling framework with a set of learned dictionaries [9]. The detection task based on DL consists in two stages: a) learning a dictionary in a supervised mode (using the label information of the training data) and, b) training a classifier using the sparse approximation of the data. Sparse approximations are representations that account for most or all information of a signal with a linear combination of a small number of elementary signals called basis vectors or atoms of the dictionary [10]. These basis vectors capture high-level patterns in the input data. The detection approach uses the sparse representation of the input data over the learned dictionary to train a classifier applied for the detection of fibrosis in a set of patients with HCM. The evaluation of the proposed method is realized by visual analysis and by comparison with other method of the literature to detect myocardial fibrosis [8].

2. Methods

The proposed approach in LGE-MRI is applied over the entire LGE-SAX image to detect enhanced and non-enhanced regions by spliting the image in several patches. Based on the DL framework, firstly, one dictionary is constructed with samples from 2 clusters (LGE and Non-LGE regions). Secondly, the sparse coefficients of the input data are computed and then used to train a K-NN classifier. Finally, the label of a test patch is obtained with its respective sparse coefficients obtained over the learned dictionary and using the trained K-NN classifier. The zones of fibrosis can be detected in the myocardium delimited by the endo- and epicardial contours. The process is divided in 4 stages.

2.1. Feature extraction

Firstly, from the LGE-SAX images, random non-overlapping patches of dimension [3×3] are extracted. Figure 1 shows an example of the feature extraction from 4 random LGE-SAX images. The non-labeled extracted patches can belong to different regions: LV and RV cavities, fibrosis and other regularly enhancing and non-enhancing structures inside and outside the heart. The similarity among the extracted patches is then calculated by using a Gaussian (radial basis function RBF) kernel with bandwidth σ.

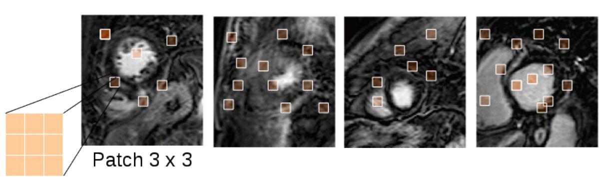

Figure 1. Feature extraction from LGE-SAX images

2.2. Clustering

The initialization of the dictionary is very important for the success of the fibrosis detection process. Due to the cost associated with the procedure, repeating random initializations is practically impossible. Thus a smart initialization is needed. We propose the construction of an initial dictionary with two classes based on an unsupervised clustering process over the similarity measures among patches. Specifically, the aim is to split the patches in two classes, each one associated respectively with LGE and non-LGE regions. For that purpose, we apply a clustering approach based on Wavelets [11] which constructs clusters from a hierarchical cluster tree. The input matrix is decomposed using the DWT function with the Haar Wavelet applied on each row of the similarity matrix.

2.3. DL-based classification: training stage

The detection of fibrosis is performed by adapting the Kernel Sparse Representation DL algorithm (KSRDL) [12] with an initial dictionary resulting from the clustering process described before where training patches are identified in two classes LGE and non-LGE patches. In the KSRDL algorithm, sparse representation is introduced from a Bayesian viewpoint assuming Gaussian prior over the atoms of the dictionary. The KSRDL model is defined as follows:

$$\min_{\boldsymbol{D},\boldsymbol{X}} \frac{1}{2}\|\boldsymbol{Y}-\boldsymbol{D}\boldsymbol{X}\|_F^2 + \frac{\alpha}{2}\textbf{trace}\left(\boldsymbol{D}^T\boldsymbol{D}\right) + \lambda\sum_{i=1}^{N}\|\boldsymbol{x}_i\|_1, \tag{1}$$

where the input signals $\boldsymbol{Y} \in R^{n\times N}$ represent a data matrix of patches where each column is a vectorised patch of dimension [3×3] (n is the signal size, N is the number of input signals or patches). $\boldsymbol{D} = [\boldsymbol{d}_1, \boldsymbol{d}_2, \boldsymbol{d}_3, \ldots, \boldsymbol{d}_K] \in R^{n\times K}$ with K atoms is the dictionary to be learned and $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N] \in R^{K\times N}$ are the estimated sparse codes of input signals $\boldsymbol{Y}$. Classification based on DL is then performed by training a K-NN classifier over the sparse training coefficients matrix $\boldsymbol{X}$.

2.4. DL-based classification: testing stage

The class label of new p test instances can be predicted using the classifier obtained in the training step and the learned dictionary $\boldsymbol{D}$. As the selected classifier is trained based on the sparse coefficients of the input data, the test data need to be represented in the same space of representation (sparse coefficients) over the learned dictionary. To this end, the sparse coefficients matrix $\boldsymbol{X}$ for the new test instances can be obtained by solving the Non negative Quadratic Problem (*NNQP*):

$$\min_{\boldsymbol{X}} \sum_{i=1}^{p} \frac{1}{2}\boldsymbol{x}_i^T\boldsymbol{H}\boldsymbol{x}_i + \boldsymbol{g}_i^T\boldsymbol{x}_i \quad s.t. \quad \boldsymbol{X} \geq 0 \tag{2}$$

where $\boldsymbol{H}_{k\times k} = \boldsymbol{D}^T\boldsymbol{D}$ and $\boldsymbol{g} = -\boldsymbol{D}^T\boldsymbol{Y}$. As the optimizations of the above problems only require inner products between the data, the sparse coding problem is solved by replacing inner products to a radial basis function (Gaussian) kernel.

Each LGE-SAX test image is represented by a grid of overlapping feature patches of dimension [3×3]. The sparse coefficients of each patch are obtained as described previously with the learned dictionary and then, the label of each patch is obtained using the trained K-NN classifier. The pixel in the middle of the submatrix [3×3] is categorized as LGE or non-LGE pixel. Finally, the LGE pixels corresponding to fibrosis zones are delimited by the endo- and epicardial borders of the myocardium.

3. Experiments and results

This study was performed in collaboration with the "Centre d'Investigation Clinique Innovation Technologique" CIC-IT 804 of the CHU-Pontchaillou in Rennes. Cardiac Magnetic Resonance (CMR) images from 11 patients with HCM were performed with a 3T Achieva clinical imager (Philips Medical Systems, Best, The Netherlands), using cardiac SENSE Coil (multicoil). LGE-Short axis (SAX) CMR images acquired in inversion recovery (IR) sequence has been used in this work. For each patient the SAX images are obtained from 16 slices covering the apical, mid-cavity and basal planes.

In the training stage, a set of 1184 non-overlapping patches from 4 random inter-patient LGE-SAX IR images at mid-diastole and at different planes are extracted in order to construct the initial dictionary. The first stage of clustering process splits the patches in two clusters of size 952 and 232 respectively. Then, the KSRDL algorithm [12] is applied in order to obtain the sparse codes of the training data that are used in the *K-NN* classifier.

Figure 2-top, shows LGE-SAX images at mid-cavity plane for three testing patients and the Fibrosis detection (Figure 2-bottom) using the proposed approach. The detected fibrosis is represented in color inside the myocardium delimited by endo- and epicardial boundaries manually delineated by a cardiologist. In a first step of evaluation, a visual analysis by a cardiologist has been performed. The proposed method is able to detect fibrosis succesfuly in 9 of 11 patients. The method misclasified LGE pixels in two patients due to the low contrast between myocardium and the inside of the LV cavity. In a second step of evaluation, our method has been compared with a method reported in the literature. The fuzzy c-means method proposed by [8] was used to compare the detected myocardial fibrosis between our method and this approach. Figure 3-top illustrates the output of the fuzzy c-means for the LGE-voxel class for the voxels into the myocardium for three patients.

The fuzzy c-means approach includes a defuzzification procedure to obtain a binary description of those pixels being part or not of fibrosis. Then, for the entire myocardium, a threshold of the LGE-class membership was varied between 0.25 and 0.5, and the curve representing the number of LGE-voxels was plotted over these varying threshold. Then the threshold value providing the most stable output (the longest portion were the number of LGE-voxels remains the same), was selected as the optimal one [13].

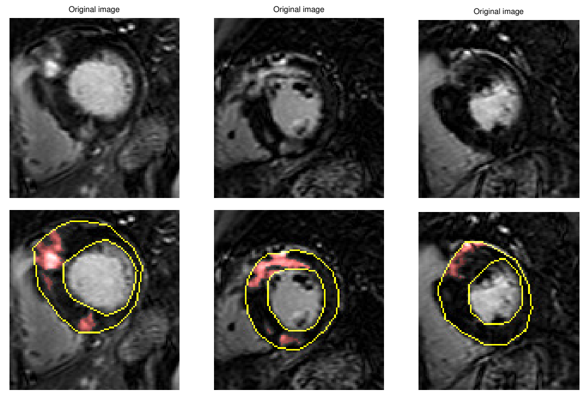

Figure 2. Top: original LGE-SAX images in three patients at the mid-cavity plane. Bottom: resulting fibrosis detection (represented in colour) in the myocardium delineated by endo and epicardial boundaries using the proposed approach

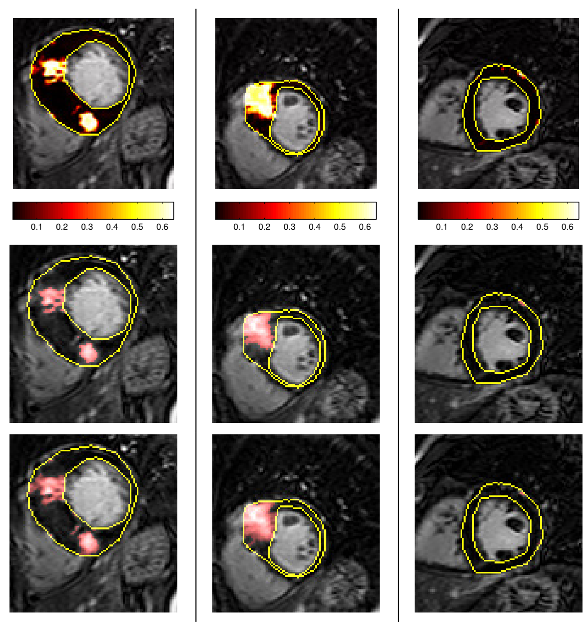

Figure 3. Examples of resulting fibrosis detection in three patients. Top: the output of the fuzzy c-means with the membership map of the LGE-class. Middle: The resulting defuzzification procedure. Bottom: The fibrosis detection using the proposed approach.

This threshold is then used to get a binary image from the output of the fuzzy c-means approach. Figure 3-middle shows the resulting detection of fibrosis for the patients on the top after the defuzzification procedure. Figure 3-bottom shows the resulting detection of fibrosis using our proposed approach. It can be noted that the fibrotic zones are accurately identified in both methods, for those regions presenting a high concentration of pixels with late gadolinium enhancement.

4. Conclusion

We have presented a method for the detection of Fibrosis in LGE-SAX images using a Dictionary learning-based clustering approach. The detection approach has been applied on a set of 11 patients with HCM from which LGE-SAX images at 16 different slices were processed. The proposed method allows the detection of fibrosis inside the myocardium using the endo- and epicardial boundaries manually delineated by a cardiologist. The method has been evaluated by a visual evaluation and by comparing with the results of one method in the literature. The method has been able to succesfully detect fibrosis in 9 of the 11 patients. The use of classification based on sparse representation of input patches from LGE images obtained with a kernel DL technique results in a powerful technique for the detection of fibrosis. The method will be extensively validated with more patients and for the quantification of fibrosis.

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References

[1] Hoey ET, Elassaly M, Ganeshan A, Watkin RW, Simpson H. The role of magnetic resonance imaging in hypertrophic cardiomyopathy. Quantitative Imaging in Medicine and Surgery October 2014;4(5):397–406.

[2] Ordovas KG, Higgins CB. Delayed Contrast Enhancement on MR Images of Myocardium: Past, Present, Future. Radiology November 2011;261(2):358–374.

[3] Gerber BL, Garot J, Bluemke DA, Wu KC, Lima JAC. Accuracy of Contrast-Enhanced Magnetic Resonance Imaging in Predicting Improvement of Regional Myocardial Function in Patients After Acute Myocardial Infarction. Circulation August 2002;106(9):1083–1089.

[4] Kim RJ, Wu E, Rafael A, Chen EL, Parker MA, Simonetti O, Klocke FJ, Bonow RO, Judd RM. The Use of Contrast-Enhanced Magnetic Resonance Imaging to Identify Reversible Myocardial Dysfunction. New England Journal of Medicine November 2000;343(20):1445–1453.

[5] Schuijf JD, Kaandorp TAM, Lamb HJ, Geest RJvd, Viergever EP, Wall EEvd, de Roos A, Bax JJ. Quantification of myocardial infarct size and transmurality by contrast-enhanced magnetic resonance imaging in men. The American Journal of Cardiology August 2004;94(3):284–288.

[6] Kolipaka A, Chatzimavroudis GP, White RD, O'Donnell TP, Setser RM. Segmentation of non-viable myocardium in delayed enhancement magnetic resonance images. The International Journal of Cardiovascular Imaging June 2005; 21(2-3):303–311.

[7] Karim R, Housden RJ, Balasubramaniam M, Chen Z, Perry D, Uddin A, Al-Beyatti Y, Palkhi E, Acheampong P, Obom S, Hennemuth A, Lu Y, Bai W, Shi W, Gao Y, Peitgen HO, Radau P, Razavi R, Tannenbaum A, Rueckert D, Cates J, Schaeffter T, Peters D, MacLeod R, Rhode K. Evaluation of current algorithms for segmentation of scar tissue from late Gadolinium enhancement cardiovascular magnetic resonance of the left atrium: an open-access grand challenge. Journal of Cardiovascular Magnetic Resonance December 2013;15(1):105.

[8] Kachenoura N, Redheuil A, Herment A, Mousseaux E, Frouin F. Robust assessment of the transmural extent of myocardial infarction in late gadolinium-enhanced MRI studies using appropriate angular and circumferential subdivision of the myocardium. European Radiology June 2008; 18(10):2140–2147.

[9] Sprechmann P, Sapiro G. Dictionary learning and sparse coding for unsupervised clustering. In 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP). March 2010; 2042–2045.

[10] Rubinstein R, Zibulevsky M, Elad M. Double sparsity: Learning sparse dictionaries for sparse signal approximation. IEEE Transactions on Signal Processing 2010; 58(3):1553–1564.

[11] Misiti M, Misiti Y, Oppenheim G, Poggi JM. Clustering signals using wavelets. In Sandoval F, Prieto A, Cabestany J, Graa M (eds.), Computational and Ambient Intelligence, number 4507 in Lecture Notes in Computer Science. Springer Berlin Heidelberg, January 2007; 514–521.

[12] Li Y, Ngom A. Sparse representation approaches for the classification of high-dimensional biological data. BMC Systems Biology 2013;7(Suppl 4):S6.

[13] Baron N, Kachenoura N, Cluzel P, Frouin F, Herment A, Grenier P, Montalescot G, Beygui F. Comparison of various methods for quantitative evaluation of myocardial infarct volume from magnetic resonance delayed enhancement data. International Journal of Cardiology August 2013;167(3):739–744.

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