



Myocardial segmentation in cardiac magnetic resonance images using fully convolutional neural networks

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ABSTRACT

According to the World Health Organization, cardiovascular diseases are the leading cause of death worldwide. Many coronary diseases involve the left ventricle; therefore, estimation of several functional parameters from a previous segmentation of this structure can be helpful in diagnosis. Although a high number of automated methods have been proposed, left ventricle segmentation in cardiac MRI images remains an open problem. In this work we propose a deep fully convolutional neural network architecture to address this issue and assess its performance. The model was trained end to end in a supervised learning stage from whole image input and ground truths to make a per pixel classification in order to segment the myocardium. For its design, development and experimentation a Caffe deep learning framework over an NVidia Quadro K4200 Graphics Processing Unit was used. Training and testing processes were carried out using 10-fold cross validation with short axis images. In addition, the performance of six optimization methods was compared. The proposed model was validated in 45 datasets of Sunnybrook database using a Dice coefficient, Average Perpendicular Distance (APD) and percentage of good contours (GC) metrics and compared with other state-of-the-art approaches. Results show the robustness and feasibility of the proposed method.

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1. Introduction

Cardiovascular diseases are the leading cause of death worldwide, accounting for 17.3 million deaths per year, a number that is predicted to increase to more than 23.6 million by the year 2030 [1]. Consequently, there is a growing demand for technology that can provide qualitative and quantitative information about the morphology and function of the heart, in order to aid in clinical diagnosis, treatment and monitoring of diseases. Currently, cardiac magnetic resonance imaging (MRI) is recognized as a reference modality for the non-invasive assessment of left ventricular function [2]. It provides a high contrast between the different soft tissues, does not use ionizing radiation and has high spatial resolution.

Regional and global cardiac function can be quantified by calculating indicators such as ejection fraction, left ventricle

myocardium mass, stroke volume and others. This task depends on accurate delineation of endocardial and epicardial contours in the left ventricle (LV), which usually is performed manually by specialists because the automated methods do not meet accuracy requirements [3]. Nevertheless, manual segmentation is a time-consuming and tedious task, which also is prone to intra- and inter-observer variability. Evidently, accurate automated segmentation of cardiac structures remains a challenge that the research community continues to grapple with.

It is important to note that algorithms face several challenges present in cardiac magnetic resonance images [2,3,4]. For example, papillary muscles and trabeculations located inside the LV cavity have the same intensity profile as the myocardium. However, according to clinical standards, they should not be considered for endocardial wall segmentation [2]. A common problem is that the LV cavity appears very small in apical and basal slices increasing segmentation complexity. Inhomogeneous intensities, artifacts caused in the process of acquisition and sudden lighting variations also affect the images. In addition, there is variability in terms of shape and appearance between different patients and pathologies.

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A large number of methodologies have been proposed for heart chamber segmentation in magnetic resonance images. Specifically, for the LV segmentation in short axis images, they can be classified as: graph-based methods [5,6], machine learning [7] and probabilistic models [8,9,10,11,12,13], deformable models [14,15,16,17,18], deep learning [19,20,21] and hybrid techniques [22,23].

Queirós et al. [24] proposed a method for myocardium segmentation based on Otsu multilevel thresholding, elliptical annular template matching algorithm and B-spline Explicit Active Surfaces framework that integrates two dedicated energy terms. In a later work, this approach was extended to 3D + time data analysis [25].

Most of the proposed methodologies are based on deformable models or use them in a complementary way. For example, Uzunbaş et al. [6] combined them with graphs in a semi-automated approach. Initially, the blood pool was segmented via graph cuts from manual initialization. To roughly segment the myocardium this same technique was used with level set applications, leading to improved results. Wang et al. [18] used a level set to delineate the endocardium and estimated the bias field which was used to decrease the intensity inhomogeneity of cardiac image. In addition, the fuzzy C-means algorithm and morphologic segmentation were applied in the corrected image to segment the epicardium. Despite its wide use, two drawbacks of deformable models remain: the initialization and parameter selection.

Wang et al. [8] and Cordero-Grande et al. [9] proposed methods based on Markov Random Fields (MRF). Similarly, Dreijer et al. [10] used Conditional Random Fields (CRF) for left ventricular segmentation. MRF and CRF are probabilistic graphical models, which have Markov properties and can express interactions between neighborhoods. They are computationally difficult due to complexity of parameter estimation [10].

Recently, deep learning based methods have emerged. Some of them continue to include deformable models as part of the methodology [19,20,22,23]. Ngo and Carneiro [19] proposed semi-automated approach that uses distance regularized level set (DRLS) and deep belief network (DBN). The latter are graphical models that learn to extract a deep hierarchical representation of the training data. They used DBN to classify many user-defined input center scaled windows to get the best region of interest (ROI). After that, they applied DRLS using the size of the selected ROI as a limit for this algorithm. Subsequently, the authors converted this to a fully automated method [20] obtaining slightly inferior results in metrics. In addition, these authors extended their previous studies [19] [20] to include epicardial segmentation [23].

Avendi et al. [22] use two deep structures: a Convolutional Neural Network (CNN) was employed to automatically detect the left ventricular cavity and stacked autoencoders to infer the shape of the LV. The inferred shape was incorporated into deformable models to improve the accuracy of the segmentation. This study, like those of Queirós et al. [24] [25], was only evaluated for endocardium contours.

According to Phi Vu Tran, “the main limitation of these recent methods is that they are multi-stage approaches that require manual offline training and extensive hyper-parameter tuning, which can be cumbersome” [21].

CNNs have achieved excellent results in visual recognition tasks applied to different areas of research such as facial expression recognition [26], digit classification [27], satellite image classification [28] and object classification [29], to name a few. Long et al. [30] adapted CNN to perform semantic segmentation. They proposed a new model named Fully Convolutional Neural Network (FCN), which replaced the fully connected layers with the fractional convolutional layers. In this model, the network is trained from an original image and its respective ground truth. The end result is a predictive map with per-pixel classifications.

Phi Vu Tran [21] was the first to apply FCN to cardiac MRI segmentation. He performed an ROI extraction assuming that the ventricular cavity was located approximately in the center of the image. This, in our opinion, can result in inaccuracies. His proposed deep architecture was trained with Stochastic Gradient Descent (SGD) optimization algorithm to left and right ventricle segmentation. Nevertheless, FCN can be trained using other optimization methods. To our knowledge, there are no other studies where these algorithms are evaluated and compared for the task of cardiac segmentation.

The aim of this work is to contribute to the state of art proposing a new FCN architecture for myocardium segmentation. Moreover, the performances of six optimization-training algorithms are compared.

This paper is organized as follows: Section 2 details database characteristics and the work environment; Section 3 and 4 explain the proposed methodology and performed experiments, Section 5 discusses the obtained results.

2. Materials

2.1. Database description

Images from the Sunnybrook [4] public dataset were used to train and validate the proposed methodology. This dataset consists of DICOM anonymized cardiac magnetic resonance images, with 256×256 pixels, which were obtained during 10 – 15 s breath-holds with a temporal resolution of 20 cardiac phases over the heart cycle, and scanned from the end diastole (ED) phase. The dataset contains several cardiac planes from 45 patients, classified in four groups representing different morphologies: heart failure with infarction (HF-I), heart failure without infarction (HF-NI), left ventricular hypertrophy (HYP) and healthy (N). This database was originally created for the Cardiac Magnetic Resonance Left Ventricle Segmentation challenge. For that purpose, the data was divided into 3 folders: training, validation and online. In all slices, endocardial and epicardial contours were drawn, at end diastole (ED) and end systole (ES) phases, by an experienced cardiologist.

2.2. Work environment

Experiments were performed in a Caffe deep learning framework [31]. The computer used was equipped with a DELL[®] motherboard with 128 GB RAM, a Intel (R) Xeon (R) processor ES-1650 at 3.50 GHz with 12 cores. The graphics processing unit used was an Nvidia Quadro K4200 model with 4 GB of RAM and 1440 CUDA cores. The computer operating system was Ubuntu 14.04 under Linux 4.2.0-36-generic kernel.

3. Methods

Initially, the images passed through a preparation stage, and then were divided for training and testing purposes. After building the network architecture, it was trained in a supervised way end to end, from whole image inputs and corresponding ground truth, to make inferences about every pixel at the output in order to segment the myocardium. Several experiments were performed with different optimization algorithms, namely SGD [32], Nesterov accelerated gradient [33], RMSProp [34], Adam [35], AdaDelta [36] and AdaGrad [37]. Finally, the test images were segmented using the trained network. In the next subsections, these steps will be discussed in more detail. An overview of the approach is shown in Fig. 1.

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