Recognition and Standardization of Cardiac MRI Orientation via Deep Neural Network

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Abstract

In reality,we always need to face the problem of imaging orientation in cardiac MRI.This paper gives a new method to propose a DNN-based framework to solve the cardiac image orientation recognition and standardization tasks simultaneously.For multiple sequences and modalities of MRI, we propose a transfer learning strategy, which adapts our proposed model from a single modality to multiple modalities.Based on the network above,we embed it into the orientation correction tool which is designed for MRI image visualization, orientation standardization and adjustment.The source code, neural network models and tools have been released and open via `https://github.com/Grit1021/CMR-Orientation`.

Keywords: Orientation recognition; Cardiac MRI; Deep neural network

1 Introduction

Nowadays,cardiac MRI are increasingly used for cardiac functional analysis in daily clinical practice.With MRI,images can be acquired in any spatial orientation.van Assen et al. (2006)Cardiac Magnetic Resonance (CMR) images could be stored in different image orientations when they are recorded in DICOM format and stored into the PACS systems. Recognizing and understanding this difference is crucial in deep neural network (DNN)-based image processing and computing, since current DNN systems generally only take the input and output of images as matrices or tensors, without considering the imaging orientation and real world coordinate.Unfortunately,due to different data sources and scanning habits,the orientation of different cardiac magnetic resonance images may be different and the orientation vector corresponding to the image itself may not correspond correctly.This may cause problems in tasks such as image segmentation or registration.

Recent works have shown that deep neural networks have been demonstrated to achieve state-of-art performance in many medical imaging tasks,such as orientation recognition and prediction tasks.Wolterink, van Hamersvelt, Viergever, Leiner, and Išgum (2019) proposed an algorithm that extracts coronary artery centerlines in cardiac CT angiography (CCTA) images using a convolutional neural network (CNN). Duan et al. (2019) combine a multi-task deep learning approach with atlas propagation to develop a shape-refined bi-ventricular segmentation pipeline for short-axis CMR volumetric images. Based on CMR orientation recognition, we further develop a framework for standardization and adjustment of the orientation.

In this paper,the problem of orientation correction in cardiac MRI images is investigated and a framework for orientation recognition via deep neural networks is proposed. With our network,one can categorize the orientation recognition and standardization for multiple CMR modalities and beneficial for further tasks.Figure 3 presnets the pipleline of our proposed method.The main contributions of this work are summarized as follows:

1. We propose a scheme to standardize the CMR image orientation and categorize all the orientations for classification.
2. We present a DNN-based orientation recognition method for CMR image and transfer it to other modalities.
3. We develop a CMR image orientation adjust tool embedded with a simplified orientation recognition network, which facilitates the CMR image orientation recognition and standardization in clinical and medical image processing practice.

2 Method

In this section,we introduce our proposed method for cardiac MRI orientation recognition and standardization.Our proposed method is built on the categorization of CMR image orientations.We propose a network framework and embed it into the CMR orientation adjust tool.

2.1 Data Preparation

For simplicity,the 3D CMR image is sliced into 2D slices,and each slice is resized to (256,256).Although this procedure results in a loss of resolution,the influence is negligible in this task.Given that we have transformed the nii images to png images,we take a 2D image as an example.

2.1.1 Data construction

Due to differences in equipment and scanning habits,for each patient there may exist 8 different directions of an MRI image.The followings show the different orientation of a single slice selected from the data after transformation(from nii to png).

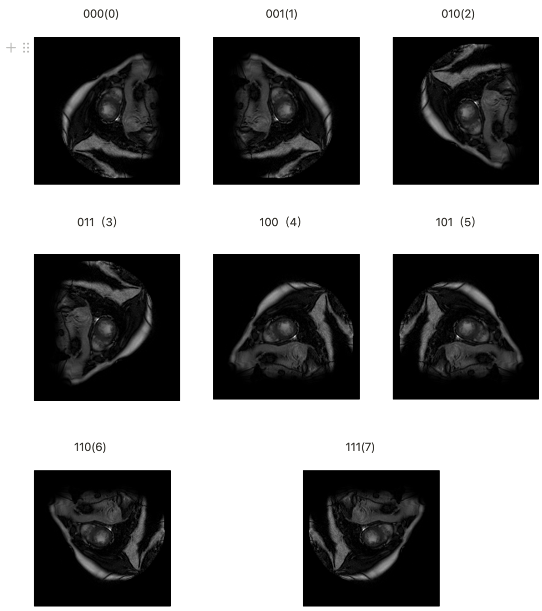

Figure 1: Patient slice

We set the orientation of an image as the initial image and set the four corners of the 2D image in standard direction ('000') as $\begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$ and the directions of the 2D image in the two-dimensional MRI image above can be written as the same forms.According to the different image directions,we give the corresponding table for the relationship between the images and directions:

Table 1: Correspondence table

label	operation	image	correspondence of coordinates
000	initial state	$\begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$	Target[x,y,z]=Source[x,y,z]
001	horizontal flip	$\begin{pmatrix} 2 & 1 \\ 4 & 3 \end{pmatrix}$	Target[x,y,z]=Source[sx-x,y,z]
010	vertical flip	$\begin{pmatrix} 3 & 4 \\ 1 & 2 \end{pmatrix}$	Target[x,y,z]=Source[x,sy-y,z]
011	rotate 180° clockwise	$\begin{pmatrix} 4 & 3 \\ 1 & 2 \end{pmatrix}$	Target[x,y,z]=Source[sx-x,sy-y,z]
100	flip along the upper left -lower right corner	$\begin{pmatrix} 1 & 3 \\ 2 & 4 \end{pmatrix}$	Target[x,y,z]=Source[y,x,z]
101	rotate 90° clockwise	$\begin{pmatrix} 3 & 1 \\ 4 & 2 \end{pmatrix}$	Target[x,y,z]=Source[sx-y,x,z]
110	rotate 270° clockwise	$\begin{pmatrix} 2 & 4 \\ 1 & 3 \end{pmatrix}$	Target[x,y,z]=Source[y,sy-x,z]
111	flip along the bottom left-top right corner	$\begin{pmatrix} 4 & 2 \\ 3 & 1 \end{pmatrix}$	Target[x,y,z]=Source[sx-y,sy-x,z]

Now we have the original dataset(adjusted) consisted of 45 patients and have the right direction '000' and we need to flip(rotate) the original image to obtain the classified image files for training.For each image-label pair (X_t, Y_t),select a target direction O_k from 8 direction classes and flip(rotate) the direction of X_t to the direction of O_k and then get the transformed image-label pair (X'_t, Y'_t).

In addition,random small-angle rotations,random crops and resize for the images also be applied for the purpose of data augmentation.

2.1.2 Data pre-processing

We also adopt a different preprocessing method. Suppose given image-label pair (X_t, Y_t), for each pair of X_t. We denote the maximum gray value as G. Three truncation operations are performed on X_t at thresholds 60%G,80%G, G to obtain X_{1t},X_{2t},X_{3t} respectively. The truncation operation maps the pixel whose gray value higher than the threshold to the threshold gray value. Setting different thresholds enforces the characteristics of the image under different gray value window widths to avoid the influence of extreme gray values. The grayscale histogram equalization is also performed on X_{1t},X_{2t},X_{3t}.We found that the equalization preprocessing of the gray histogram can make the model converge more stably during training. We denote the concatenated 3-channel image $[X'_{1t}, X'_{2t}, X'_{3t}]$ as X'.

2.2 Network structure

Deep learning-based methods have been widely used in orientation recognition and prediction tasks.We proposed a combination of networks to complete multiple tasks to access the orientation recognition,standardization and adjustment together.The network architecture in Figure 2 shows that it consists of 3 layers of CNN to generate feature maps.

2.2.1 Combination of networks

We start with the orientation recognition network,where we are interested in take segmentation masks.The orientation recognition network is embedded into the orientation adjust tool to generate the feature maps and perform classification based on the aggregated feature maps.The backbone we selected are 3-layer CNN and ResNet proposed by He, Zhang, Ren, and Sun (2016) respectively,and according to the similar accuracy,we finally determine CNN as backbone due to its simplicity and efficiency.The following is the backbone for the recognition network:

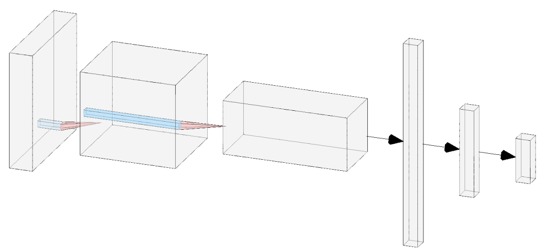

Figure 2: Network backbone

On the basis of the orientation recognition,the CMR images tranfer into the orientation adjust tool for orientation correction of the CMR images.The command-line tool, which supports batch orientation standardization operations of CMR images and provides a simple parameter setting method. By specifying a folder, one line of command is enough to identify the orientation of all MRI files in the folder and correct the files with the wrong orientation.The follwoing is the pipeline of the whole process:

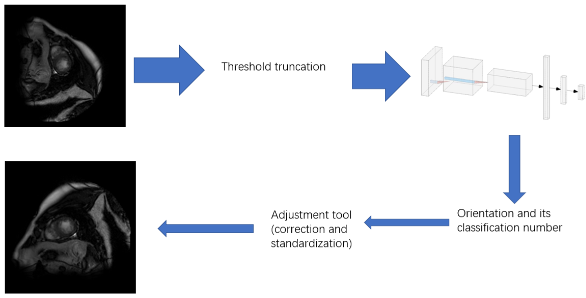

Figure 3: Orientation task pipeline

2.2.2 Network training

After data preprocessing,we use Resnet and DNN respectively to train the network.On the basis of the pre-processing datasets,we first process data augmentation and follow network training.The network was trained with the following parameters:0.01 learning rate,40 epochs,32 batch size,SGD optimizer and CrossEntropyLoss with default parameters.

Considering the dataset is consisted of multi modalities,we adopt a transfer learning method to obtain the transferred model when adapting the proposed orientation recognition network from a single modality to other modalities.For example, we pre-train model on the balanced-Steady State Free Precession (bSSFP) cine dataset and then transfer model to late gadolinium enhancement (LGE) CMR or the T2-weighted CMR dataset.In transfer training,we fix the parameters in network and retrain the connected layer on the new modality dataset.We then go to the next fine-tune step which retains the encoder and fully connected layer parameters on the new modality dataset until the model converges.

3 Experiment and results

We perform the training process and evaluate our proposed network for orientation recognition on the MyoPS dataset cited from Zhuang (2016).The MyoPS dataset not only provides the three-sequence CMR(LGE,T2,and bSSFP) and three anatomy masks, including myocardium (Myo), left ventricle (LV), and right ventricle (RV) but also provides two pathology masks (myocardial infarct and edema) from the 45 patients.

Without the loss of generality,we split our dataset into training and test sets by 4:1.For comparison,we also list the results obtained from ResNet18 and operational DNN.Table 2 shows the average accuracy on the data set with different methods.The sufficiently high accuracy results provide us with the evidence that our model is efficient.

Table 2: Experiment result table

Method	Modality accuracy			Notes
	bSSFP	LGE	T2	
ResNet	0.9995	0.9906	0.9883	pre-train(bSSFP)+transfer learning(LGE+T2)
DNN(optional)	0.9930	0.9457	0.9527	pre-train(bSSFP)+transfer learning(LGE+T2)
DNN(proposed)	0.9967	0.9787	0.9693	pre-train(bSSFP)+transfer learning(LGE+T2)

4 Implications and discussion

In this paper,we propose a DNN model for CMR orientation recognition and standardization.In addition, we have developed the CMR Orientation Adjust tool, which is embedded with an orientation recognition network. The experiment demonstrates that the embedded orientation recognition network is capable of recognizing the orientation classification from multi-sequence CMR images and outperforms compared with optional DNN. Our future research aims to improve the categorization accuracy of the CMR image orientation and refine orientation standardization on 3D MRI images.

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Supplementary Materials (optional)

The complete codes of the project can be accessed via the following URL:https://github.com/Grit1021/CMR-Orientation.