Recognition and standardization of cardiac MRI orientation with deep neural networks

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Abstract. In this paper, we study the orientation recognition and standardization of Cardiac Magnetic Resonance (CMR) images. The required dataset is constructed by performing orientation changes on the standard atlas. We first propose a deep neutral network to recognize orientation on LGE set. Then we adopt the transfer strategy to adapt our proposed model from single modality images to multiple modality images. Finally, the recognition neutral network is embedded in the Cardiac MRI Orientation Adjust Tool, i.e., CMRadjustNet, which supports MRI image visualization, orientation prediction, adjustment, storage operations and batch operations.The source code, neural network models and tools have been released and open via https://github.com/qin1114/1-MSCMR-orient.

Keywords: Orientation recognition · Transfer learning · Cardiac MRI

1 Introduction

Cardiac Magnetic Resonance (CMR) images could be stored in different image orientations when they are recorded due to personal habits of doctors or various sources. However, current DNN systems, which are generally sensitive to location information, only take the input and output of images as matrices or tensors, without considering the imaging orientation and real world coordinate. So it's crucial to recognize real world coordinate in advance and standardize them to guarantee robustness and accuracy of results.

Orientation standardizaion and image segmentation are prerequisites for doctors to diagnose diseases, which generally consume lots of manpower and material resources. Since deep neutral network has made breakthroughs in many tasks of medical imaging, we propose a study of the CMR image orientation, for reference to the human anatomy and standardized coordinate system of real world, to develop an efficient method for recognition and standardization of the orientation.

To enable the proposed model to be conveniently applied in medical image processing and clinical practice, we develop a CMR Orientation Adjust Tool, which is referred to as the CMRadjustNet Tool or CMRadjustNet in the remaining of the article for simplicity. CMRadjustNet supports batch orientation

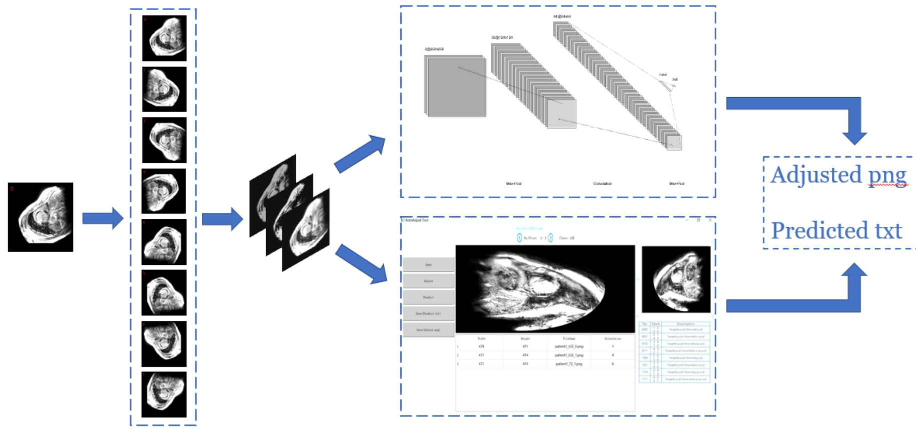


Fig. 1: The pipeline of the proposed CMR orientation recognition and standardization method. The image is first truncated at several gray value thresholds. Then the processed image is used to generate the image-orientation pair (see section2.1). Then, the orientation recognition network is embedded to the orientation adjust tool.

adjustment and prediction on pictures on png or jpg format, and the results are stored in png format and txt format respectively by save button.

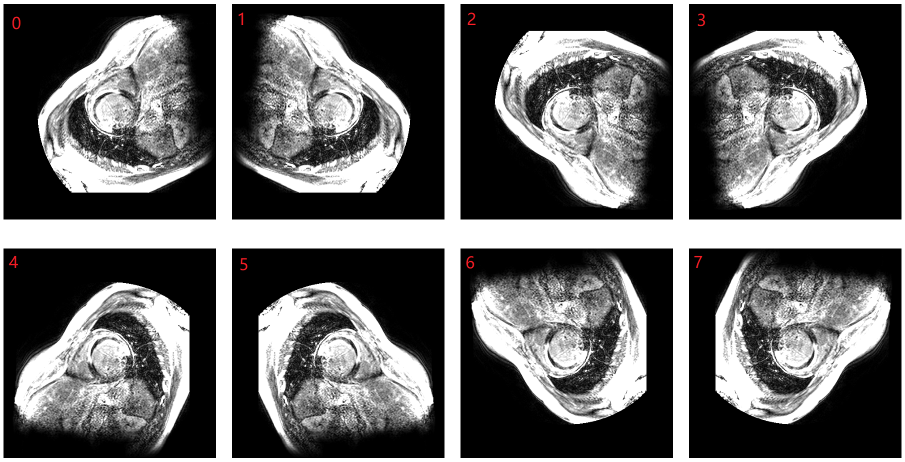
This work is aimed at designing a DNN-based approach to achieve orientation recognition and standardization for multiple CMR modalities. Figure 1 presents the pipeline of our proposed method. The main contributions of this work are summarized as follows:

(1) We perform data preprocessing on the standard data set, and randomly generate the required image-orientation pair for model training.
(2) We propose a deep neutral network to predict the orientation of single modality CMR images, and propose a migration strategy to apply the results to multiple modalities.
(3) We develop a CMR Orientation Adjust Tool embedded with proposed orientation recognition network, which supports MRI image visualization, orientation prediction, adjustment, storage operations and batch operations.

2 Method

In this section, we introduce the details of our proposed model. We first obtain the target image-orientation data set based on changing orientations of standardized CMR images(Shown in Figure 2). We propose a CNN to predict orientations and embed it into the CMR Orientation Adjust Tool,i.e., CMRadjustNet.

Fig. 2: The 8 Orientation class of a given 2D slice of CMR image



CMR Image Orientation Categorization Due to different data sources and scanning habits, it's inevitable that orientation of cardiac magnetic resonance does not match real orientation. Although there exists some tricks, such as image enhancement, to reduce the sensitivity of neural network to location information, we hope to standardize orientation in data preprocessing to solve this problem from the root. For lack of labeled data set, we first perform eight orientation changes on the standardized image to obtain the target image-orientation data set. Since the image may not be equal in length and width, we take the $\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$ matrix as an example. Then the orientation of the 2*3 matrix may have the following 8 variations, which is listed in Table 1 Given a 2D MR image-label pair (X_t, Y_t), we denote the predicted orientation as O_t.

Table 1: Orientation Categorization of 2D CMR Images. Here, sx, sy and sz respectively denote the size of image in X-axis, Y-axis and Z-axis.

No.	Operation	Image	Correspondence of coordinates
000	initial state	1 2 3 4 5 6	Target[x,y,z]=Source[x,y,z]
001	horizontal flip	3 2 1 6 5 4	Target[x,y,z]=Source[sx-x,y,z]
010	vertical flip	4 5 6 1 2 3	Target[x,y,z]=Source[x,sy-y,z]

011	Rotate 180° clockwise	6 5 4 3 2 1	Target[x,y,z]=Source[sx-x,sy-y,z]
100	Flip along the upper left−lower right corner	1 4 2 5 3 6	Target[x,y,z]=Source[y,x,z]
101	Rotate 90° clockwise	3 6 2 5 1 4	Target[x,y,z]=Source[sx-y,x,z]
110	Rotate 270° clockwise	4 1 5 2 6 3	Target[x,y,z]=Source[y,sy-x,z]
111	Flip along the bottom left−top right corner	6 3 2 5 4 1	Target[x,y,z]=Source[sx-y,sy-x,z]

Orientation Recognition Network In our work, we propose a CNN with 3 convolution layers, two fully connected layers and a unique average pooling layer. Also we adopt a novel preprocessing method to concatenate input channels into 3. Finally we propose a transfer learning strategy tp adapt our proposed model from a single modality to multiple modalities.

Here are some details:

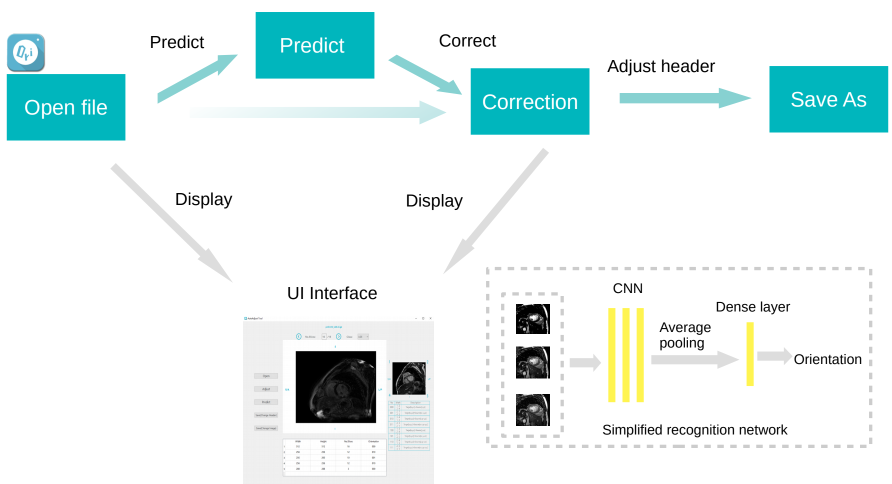
- preprocess and image augmentation: Suppose given image-label pair (X_t, Y_t) , for each pair of X_t. We denote the maximum gray value as G. Three truncation operations are performed on X_t at thresholds $60\%G, 80\%G, G$ to produce X_{1t}, X_{2t}, X_{3t} respectively. The truncation operation maps 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} to obtain $X'_{1t}, X'_{2t}, X'_{3t}$. 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. Then, we randomly divided all slices into the training set, validation set and test set at the ratio of 80%, 10% 10%. Finally, we perform image augmentation skills including random crop and random rotation only on training set and validation set.

- transfer strategy: First, we train our proposed 3-layer CNN model with 40 batchs, batch size 32, SGD optimizer with default parameters and a learning rate of 10^{-2} on late gadolinium enhancement(LGE) CMR set.

When adapting the proposed orientation recognition network from a single modality to other modalities, we adopt a transfer learning method to obtain the transferred model. We load parameters pre-trained and fix the network parameters except for the last fully connected layer. Retrain our model with 10 batchs, batch size 64 and a learning rate of 10^{-3} on T2-weighted CMR set and the balanced-Steady State Free Precession(bSSFP) CMR set. We go to the next fine-tune step until the model converges. In the fine-tune training, we retrain the encoder and fully connected layer simultaneously on the new modality dataset to obtain an adapted model.

CMR image orientation adjust tool To enable the proposed model to be conveniently applied in medical image processing and clinical practice, we develop a DNN-based CMR image orientation adjust tool, which is embedded with our proposed model. CMRadjustNet supports batch orientation adjustment and prediction on multi-model CMR images, and could store the results into png format and txt format respectively, independent of the python environment. Figure 3 presents the pipeline of the proposed CMR image orientation adjust tool. As to visualization, Users could get instant update of information such as filename, current slice index, image catalogue and so on.

Fig. 3: The pipeline of the proposed CMR image orientation adjust tool.



3 Experiment

We evaluate our proposed orientation recognition network on the MyoPS dataset [2,3], which provides the three modalities CMR (LGE, T2, and bSSFP) from the 45 patients. We divide all slices into two subsets, i.e., training set, validation set, and test set with proportions of 80%, 10% and 20%, respectively. In each training iteration, a batch of the three-channel images X is fed into the simplified orientation recognition network. We first apply our proposed model on LGE dataset and store parameters of model. Then we adopt transfer strategy on bSSFP and T2 dataset, which show less time and higher test accuracy, from which we believe our model is relatively reliable.

Fig. 4: Model result of 2D MS-CMR.

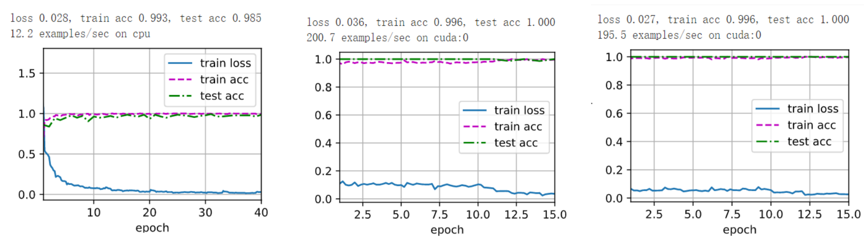


Figure 4 and Table 2 show the average accuracy on the data set. The description indicates whether the model was trained on this modality or was transferred from other modalities. The high accuracy results provide us with the necessary conditions for the development of the CMR image orientation adjust tool.

Table 2: Orientation recognition accuracy of 2D MS-CMR.

Modality	Accuracy	Description
bSSFP	0.985	pre-train
LGE	1.000	transfer learning
T2	1.000	transfer learning

4 Conclusion

We have proposed a 3-layer CNN and transfer strategy for multi-sequence MRI images that deal with orientation recognition. Also, we have developed the CMR Orientation Adjust tool (CMRadjustNet), which is embedded with the orientation recognition network. The experiment demonstrates that the embedded orientation recognition network is capable of recognizing the orientation classification from multi-sequence CMR images. Our future research aims to expand the categorization of the CMR image orientation, and study orientation standardization on 3D MRI images.

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