Cardiac MRI Artifact Reduction by Deep Image Prior

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***Abstract*—Artifact reduction is an essential task for cardiac segmentation and assisting diagnosis. A pacemaker in cardiac causes artifacts in magnetic resonance images(MRIs). Image inpainting methods can be relevant to this obstacle. Deep learning approaches that are used for image inpainting require large data and computation time. To the best of our knowledge, we first utilize "the deep image prior"(DIP) method on cardiac MRIs that does not need a long training process [6]. We use quality images as prior knowledge to reconstruct MRIs that have artifacts in a short time. Cardiac images can be invariant because of the moving of the heart, so it is difficult to find the right angle. To find a proper prior image, we employ clustering and image matching methods to quality images. Our method shows satisfying refinement on image segmentation.**

***Index Terms*—Cardiac, MRI, Artifact reduction, Segmentation, Pacemaker**

I. Introduction

At first, image inpainting is mostly used for recovering old images and removing unwanted objects; but later it starts to be used for image processing techniques. It is a technique that modifies images with missed or damaged parts. The missing parts can be filled with the information surrounding them or the damaged parts are deleted by using a mask and filled again [1]. There are several ways to do image inpainting. A review study examines them under three headings as sequential based, convolutional neural networks(CNN) based and generative adversarial networks(GANs) based approaches [2]. Nowadays CNN and GAN are very popular computer vision tasks, but they need large datasets and long training processes. Deep image prior method downsamples image through a network and reconstructs it with this prior knowledge [6]. A prior image is sufficient for reconstructing and refining a corrupted image. In a previous study, CNN used for reducing the pacemaker artifact, but we first use the deep image prior method on cardiac MRIs [7]. Our main contribution is designing an end-to-end model that cluster images on a database and select the best suitable image as a prior. Then reconstruct the artifact image for better segmentation.

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II. Methods

Our architecture consists of 2 clustering modules followed by a siamese network. There is "the deep image prior" network at the end of the architecture like in figure 1.

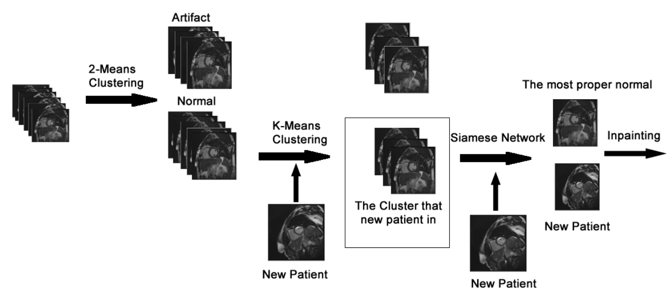

Fig. 1. Cardiac MRI artifact reduction architecture.

A. Clustering Images

In our model, images are converted to a one-dimensional vector, then we apply principal component analysis(PCA) to represent sparsely. We use the K nearest neighbor algorithm for clustering [4].

B. Siamese Network

Siamese network is a successful model for face verification problems [5]. In this model, images are represented by embedding vectors. The model decides these two images are matching or not by calculating distances between the embedding vectors. In the training process, 3 images are used. They are anchor, positive and negative. The selection of these images is an important task. The model tries to optimize triplet loss:

$$L = max(d(a,p)d(a,n) + margin, 0) \tag{1}$$

where a is anchor, p is positive, and n is negative samples.

C. Image Inpainting

DIP is an efficient way for image inpainting without long training time. The CNN based generator network is applied to a random vector z to map image x:

$$x = f\theta(z) \tag{2}$$

The model focuses on where the distribution is conditioned on a corrupted observation x_0 to solve inverse problems like inpainting. In an image inpainting application with DIP, a binary mask $m \in 0,1^{H*W}$ is applied to the image for acquiring a holed image x_0. The corresponding data term is given by:

$$E(x; x_0) = ||(x - x_0) \circ m|| \tag{3}$$

where $\circ$ is Hadamard's product

D. Training and Evaluation

The model optimizes mean squared error during training:

$$MSE = (\frac{1}{n}) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{4}$$

In this project, we use U-Net architecture which is well-known for its application on medical images as an auto-encoder. It consists of downsampling and upsampling paths, each step includes a convolutional layer followed by batch-normalization and ReLU as activation layers. The two-stride max-pooling layers are applied for the down-sampling stage. We considered three down-sampling and up-sampling blocks with skip connections between each down-sampling and up-sampling blocks to transfer the local information. There is no chance to use ground truth images for this application, so results can be evaluated visually or segmentation success.

III. Experiments and Results

A. Model Selection

Firstly we divide our cardiac MRIs into two groups as normal and artifact images because we need an image that can be used as prior. The 2-NN clustering algorithm is used for the first module. After clustering, we get normal images. We expect to find a proper image in this group. We put the new patient's MRI into this group and cluster again to divide subparts. We select the group which the patient's image in like in figure 1. Then we give these images to the siamese network. After we find, the prior image we apply the deep image prior method. The generally used deep models ResNet, SkipNet, and U-Net are tested in DIP and results are compared in figure 2.

We focus left ventricular that is depicted in red circles in our experiments. This experiment shows SkipNet is the best model for our task.

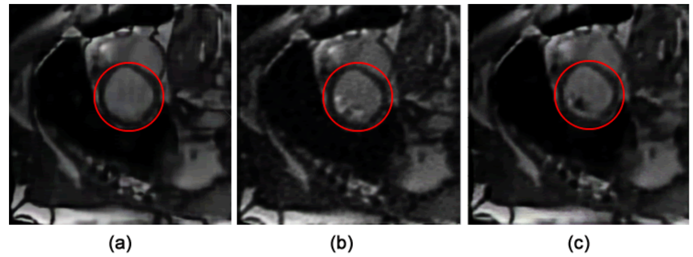

Fig. 2. Results of the model comparison . (a) SkipNet, (b) ResNet, (c) U-Net

B. Clustering

We apply 2-NN clustering to separate normal and artifact images. We convert our images 160*160 vector than apply PCA to represent images with 5 principal components. We can separate normal and artifact images. Then we use 3-NN clustering by including new patients image for reducing complexity of image matching. The next task is to find the closest normal image to the new patient's image by the siamese network.

C. Image Inpainting

After we find the best image, we apply the binary mask before we seed the DIP model like in figure 3. We train SkipNet 500 epochs with learning rate of 0.01.

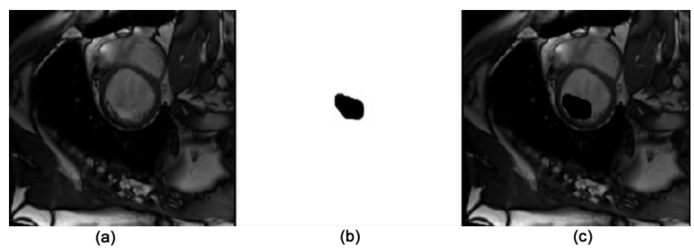

Fig. 3. Masking operation (a) Normal, (b) Mask, (c) Corrupted

Corruption and inpainting operations take nearly 3 minutes. The model is trained with Nvidia GT 1050 GPU. The generator model starts with a random image and epoch by epoch results get better. The model fixes the input image and updates theta parameters. Sufficient results occur after 500 epochs.

D. Segmentation

IV. Conclusion

In this study, we try to solve Cardiac MRI artifact reduction caused by a pacemaker. Deep learning models like partial convolutions are successful at image inpainting but they require large data and long training time [3]. We develop an end-to-end model for this problem. We show that DIP model that no need training may be beneficial to this problem. We need only 2 images to run the model. In DIP model, different architectures can be used but we find SkipNet convenient after our model selection experiment. We use image clustering and siamese network for selecting the prior image. These ensemble models help performance. Reconstructed image quality can be

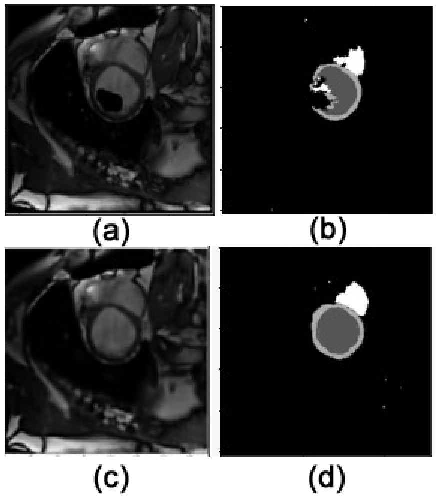

Fig. 4. Segmentation results . (a) Corrupted image, (b) Segmentation of corrupted image, (c)Reconstructed image with our architect, (d) Segmentation of reconstructed image.

realized visually. We also apply segmentation operations to show the difference between the corrupted and reconstructed image after the model. Our results show a good performance in a short time.

Acknowledgment

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks …". Instead, try "R. B. G. thanks…". Put sponsor acknowledgments in the unnumbered footnote on the first page.

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