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Medical image Synthesis with improved Deep Convolutional Bi-Generative Adversarial Network Aided Genetic Algorithm

Neeraj Varshney, Narendra Mohan
Department of Computer Engineering & Applications
GLA, University, Mathura, India-281406
neeraj.varshney@gla.ac.in ,narendra.mohan@gla.ac.in,

Article Info
Volume 82
Page Number: 56 - 63
Publication Issue:
January-February 2020

Article History

Article Received: *14 March 2019*
Revised: *27 May 2019*
Accepted: *16 October 2019*
Publication: *01 January 2020*

Abstract
In different clinical applications, important role is played by Medical imaging. Acquisition of various image models are limited by radiation lose and cost considerations. Desired image modality are estimated by medical image synthesis without original scan. To address this issues, generative adversarial method is proposed in this research. For a given source image, target image is generated by training fully convolutional network (FCN).
Better model of FCN is obtained by using adversarial learning method. Mapping of source to target imaging is done in an effective way by this and highly accurate target images are produced by this. Generation of target images with blurring is avoided by incorporating loss function with image-gradient-difference in the design of FCN. Network is trained using Long-term residual unit. Deep convolutional adversarial network with context awareness is created by applying Auto-Context Model (ACM).
Deep Convolutional GA connected with bi-generative adversarial network (DC-Bi-GAN) is implemented for synthesizing images. From source images, target images are accurately synthesized by proposed model and it is more robust as shown by results of experimentation. From MRI, CT is generated and from 3T MRI, 7T MRI are generated using this model with three datasets. In all task and dataset, superior results are produced by proposed model.

Keywords: *Generative Adversarial Network, Residual Learning, Image Synthesis, Deep Learning, Auto-Context Model, Adversarial Learnin*

1 Introduction

In planning radiotherapy, Computed tomography (CT)-based radiotherapy is used widely and it is an effective method. Compared with CT scan, superior contrats of soft tissue are given by magnetic resonance (MR) imaging. So, developed a MR imaging based radiotherapy devices. In organs, ligaments, soft tissues, very slight differences are detected using MR imaging in an effective way. But MRI is too costly and requires more time. For example, CT requires only 5 min, while 30 min is required by MRI. MR imaging procedure is contraindicated due to artificial joints, cardiac pacemakers. Due to high cost, few patients are nor adapting this.

It requires certain modality and in practice, it is not feasible, as mentioned above. From various sources, image can be synthesized by a system. It is done by acquisition protocols and image modalities. For clinical usage, imaging data can be provided by this. It does not require any additional cost or real acquisition. It difficult to solve directly medical image synthesis. Mapping of source and target images is highly dimensional one. MRI and CT images are having various appearances as shown by figure 1 a and 1 b.

Mapping of MRI and CT image is a non-linear task. Model has to put lot effort in bridging significant gap in appearance. Compared with 3T MRI, high contrast and resolution is contained by 7T MRI as shown in figure 1 c. So mapping of 7T MRI from 3T MRI is a challenging task. To address this issue, various models are developed in recent days by various researchers. Berker et al. [1] formed various classes of tissues by segmenting MRI images in order to make MRI-to-CT problem as a task of segmentation. Known attenuation property is assigned to every class.

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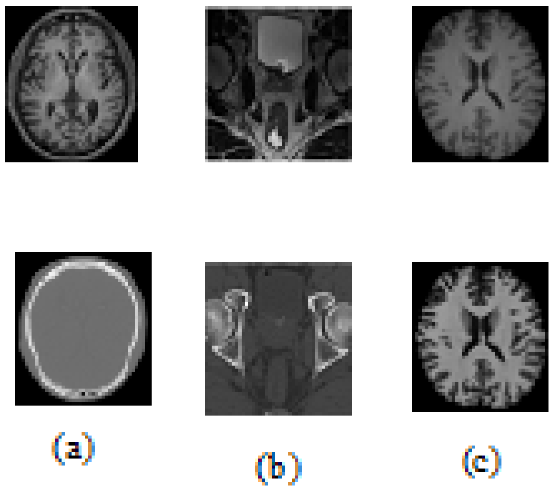

Fig. 1. Three pairs of corresponding source (left) and target (right) images from the same subjects. (a) shows a pair of MRI/CT brain images; (b) shows a pair of MRI/CT pelvic images; (c) shows a pair of 3T/7T brain MRI.

Accuracy of segmentation defines this method. Accuracy of result requires manual computation. In literature, atlas-based methods are used. New subject's source image is register an atlas in [2] and target image is estimated by wrapping atlas of corresponding target image. Label Propagation (LP) segmentation algorithm is extended in [3]. It is called as Modality Propagation.

LP generalization is allowed by this and it works with continuous data. It does not require labels categorical segmentation. Information propagation method is proposed in [4]. In source dataset, similar patches of specified source path is searched by system. According target, target images are constructed.

Accuracy of registration defines the accuracy of atlas-based methods. Mapping of source to target image can also be done with learning-based methods. It rectifies various drawbacks previous works [5]. , Jog et al. [6] performed cross-modality synthesis by nonlinear regression in high resolution images with random forest from low resolution scans.

Huynh et al. [7] used random forest to map MRI to CT. They used unsupervised methods also. Zhao et al. [8] synthesized CT from MR image using a modified U-Net [9]. Segmentation of brain is done using this synthetic MR image. In output blurs are generated by minimization of voxel-wise loss in training between reference and synthesized image.

Nie et al. [10] produced clear results by combining adversarial loss and voxel-wise loss of generative adversarial network (GAN). Positron emission tomography (PET) images are synthesized using a similar method from CT images [11]. Isola et al. proposed pixel-to-pixel (pix2pix) framework by using various information from different channels [12].

Ben-Cohen et al. [13] exported initial results by combining pix2pix model and fully convolutional network (FCN) [14]. From CT image, synthesized PET image is generated by blending two outputs. Blurry generated synthesis problem is addressed by combining adversarial loss and of voxel-wise loss. Large number of MR and Ct images which are aligned defined voxel wise lose.

It is expensive as well as difficult to get aligned data. Generated a set of target candidate values for every voxel in source image in a framework proposed in [15]. In target image's training set , nearest neighbours are searched for the same. Paired data is not used. Similarity measures are used to face the changes in modality. Mutual information is also used in this conditions. Global energy function is maximized for selecting best candidates. Between target and source, mutual information is also considered.

Source images are represented by features and target images are generated by mapping those feature. Representation of source image and manually engineered features defines performance this method. In medical image analysis and computer vision, deep learning is getting popular. It does not require any hand-crafted features for producing better results [16]. Dong et al. [17] used Convolutional Neural Networks (CNNs) for single image super-resolution. Kim et al. [18] proposed recursive CNN for improving super-resolution algorithm. Parametric complexity is not increased while boosting performance.

Li et al. [16] estimated missing PET by applying deep learning model from MRI data. Huang et al. [20] conducted synthesis of cross-modality and super-resolution medical image simultaneously. It is done by joint convolutional sparse coding which is weakly supervised. In the prediction of target image, neighbourhood information are neglected in CNN.
For image synthesis, structural information is preserved by Fully Convolutional Networks (FCNs) [21]. FCN and CNN are trained using a loss function computed by L2 distance which is predicted between original and target image. In multi-modal distributions, target images are

blurred [22]. Peak signal-to-noise rate (PSNR) is maximized by reducing L2 loss. But better results are not produced by high PSNR [23].

To address this issues, generative adversarial method is proposed in this research. For a given source image, target image is generated by training fully convolutional network (FCN).

Better model of FCN is obtained by using adversarial learning method. Mapping of source to target imaging is done in an effective way by this and highly accurate target images are produced by this. Generation of target images with blurring is avoided by incorporating loss function with image-gradient-difference in the design of FCN. Network is trained using Long-term residual unit. Deep convolutional adversarial network with context awareness is created by applying Auto-Context Model (ACM).

Deep Convolutional GA connected with bi-generative adversarial network (DC-Bi-GAN) is implemented for synthesizing images. From source images, target images are accurately synthesized by proposed model and it is more robust as shown by results of experimentation. From MRI, CT is generated and from 3T MRI, 7T MRI are generated using this model with three datasets. In all task and dataset, superior results are produced by proposed model.

2 Proposed Methodology

A deep convolutional adversarial network framework is proposed to address the above mentioned challenges. In this generator corresponds to FCN and discriminator corresponds to CNN. From source images, target images are estimated by 3DFCN. 3D spatial mapping is enhanced by adapting 3D model. Across 2D slices, problems of discontinuity are solved by this. Network is designed by using adversarial learning technique. Extra discriminator network is modelled. This makes the generator output equals the target image.

In this los function is incorporated with image gradient difference. This is done to maintain generated target image's sharpness. Network is trained using the long-term residual unit. Generator output is refined iteratively by using ACM. Overlapping patches are formed by splitting input source image in testing phase. Generator estimates the target for every patch. Source-to-target synthesis is completed by merging all target patches that are generated into a single image. Overlapping CT region's intensities are averaged to perform this.
Source-to-target image synthesis used in Bi-GAN framework is described in following section. Figure 1 shows the proposed method's overall structure. It has Bi-GAN with GA. From a large set covering large area, parameters are optimized by using Bi-GAN. From a small set of choices,discrete decisions are made by using GA. Activation functions are included in choice making. Usage of batch normalization, max pooling and dropout are decided. Number of dense and convolutional layers and convolutional layer kernel size are computed.

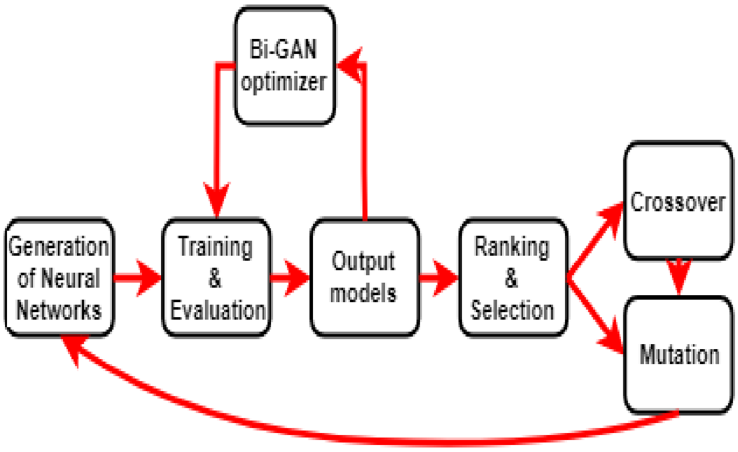

Fig. 1: Proposed Bi-GAN aided GA network for refining deep neural network parameters.For GA, network i's parameter set is given by,

$$p_i^{GA} = \left[pr_i^{con\,v^1}, \dots, pr_i^{con\,v^C}, pr_i^{dens\,e^1}, \dots, pr_i^{dens\,e^D}\right], i \in \{1,2,\dots,n_m\}$$

Where, parameter is represented by pr, convolution layer is represented by convand dense layer is represented by dense, maximum number of possible convolutionallayers is given by C and maximum number of possible dense layers is given by D, numberof network models in population is represented as n_m.

Bi-GAN network:Generative adversarial network (GAN) which is a modified as well as novel network is proposed. It termed as Bi-GAN. From large range of values, optimum network parameters are computed. Figure 2 shows the proposed Bi-GAN network. Various neural network parameters are refined by this network. There are discriminator, evaluation part and generative part. It has one discriminator (D), two evaluators ($E_1$and E_2) and are two generators ($G_1$and G_2). Gaussian noise $z \sim p_{noise}$ (z)is given as input to two generators. Training datax $\sim p_{data}$ (x) is given as input to evaluators.

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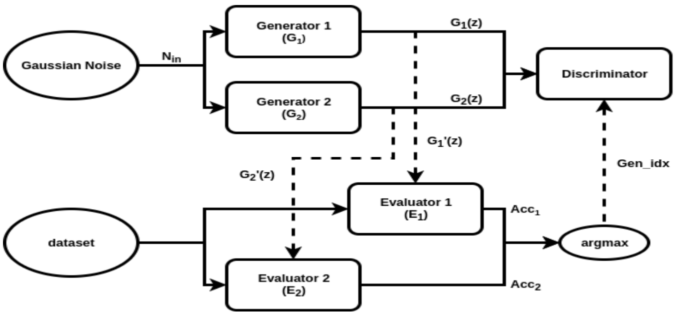

Fig. 2: Proposed Bi-GAN incorporating two generators and one discriminator.

Number of filter in convolutional layers are optimized or set by using proposed Bi-GAN in every GA evolution. For dense layer, number of neurons are optimized or set by this. Accuracy score are computed by training and evaluating the network models. GA is applied based on this score.

1) Initial Population: Randomly generate, network of first generation. Randomly choose the dense and convolutional parameters in order to generate network from available choices.
2) Bi-GAN optimization: For fully connected layers, number of neurons are updated using proposed Bi-GAN and for convolutional layers, number of filters are updated in n_m network models.
3) Evaluation: Fitness function is used to evaluate every generated model of network, after computing number of neurons and filters for fully connected and convolutional layers. Every models accuracy is computed by fitness function.
4) Selection: From sorted E, top ranked t models are selected and from rest of network models, select many models. In order to avoid over fitting, drop d models and this is also used avoid stuck with local optimum. Parent models P corresponds to remaining selected models. For next generation, new models are created by using this models.
5) Crossover and Mutation: From parents, n child network models are generated by applying crossover operation. Crossover operation is applied to generate child network. Parent counter are incremented by one. From parent pool, randomly select, two parents with zero counter value. using crossover, generate another network and parents count is incremented.
6) Network model with zero count and if number of children is still less than n_m, parent model is selected as this model. From the model with counter value one, another model is selected as parent. If there is no model with counter zero, select two models with counter value one as parent model. Until reachingn$_m$ number of children nodes, this process will be repeated.

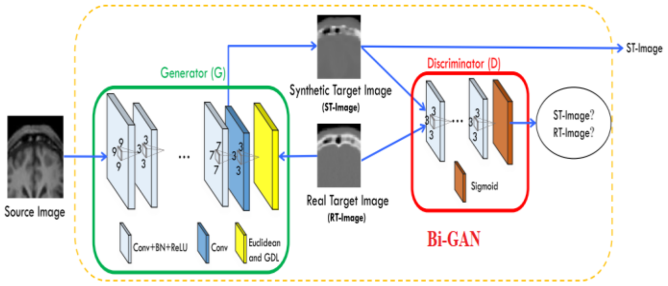

Fig. 3. Architecture used in the deep convolutional adversarial setting for estimation of the synthetic target image.

A supervised deep convolutional adversarial framework is proposed, it is inspired by recent popular Bi-GAN,to complete the source-to-target synthesis as shown in Fig. 3.Fully Convolutional Network (FCN) for Medical ImageSynthesis: For segmentation, FCN is used commonly and reconstructionin both computer vision and medical image analysisfields. In localneighbourhood of image space, spatial information can be preserved by this. Compared to CNN, it provides faster results in testing stage. Image generator is implemented by adapting FCN. Medical image synthesis task is performed by using proposed typical 3D FCN. Weuse convolution operations without pooling, whichwould potentially lead to loss of resolution.

Learning of Adversarial: For making generated target imagesbetter perceptually, we propose to use adversarial learning toimprove the performance of FCN. In the fieldof image generation better results are produced by GANs, by producing very realistic images in anunsupervised setting. Medical images are synthesized by supervised GAN. In this, target image is estimated using generator and generated and original images are discriminated by discriminator. It is shown by figure 2. Generator network G corresponds to FCN. Discriminator network D corresponds to CNN. Probability of input image being drawn from distribution of real images is estimated by this. Inputimage is classified as “real” or “synthetic” by D.

Details of Architecture: Figure 3 shows generator network’s architecture G. where numbers indicate filtersizes. This network takes a source image as input, and triesto generate the corresponding target image. The architecture isdesigned with empirical knowledge from the widely-used FCNarchitectures. Network’s input size is 32×32×32and 16 × 16 × 16 is output size, and in network inference, size of feature map has to be reduced. If we keepusing 3 × 3 × 3 as the kernel size, we will have too many layers. In training physical memory andoptimization is more challenging.Thus, we choose several big kernels todecrease the depth of the network in the generator. Our kernelsize setting is empirical, and we believe that other possibleconfigurations can also be used. There are 9 layers in this including ReLUoperations, batch normalization (BN) and convolution.

One convolutional layer is included in last layer. Estimate of target image corresponds to the output of it. Pooling is not used. Feature map's spatial resolution is reduced by pooling. Effective receptive fields are not guaranteed by generator's traditional convolution operation as shown in figure 2. So, in order to obtain enough receptive filed, dilated convolution is adapted. In Figure 2, 1 and 2 are the generator's first and last convolutional layer's dilation.

Typical architecture of CNN corresponds to discriminator D. It has three convolutional stages. They are max pooling, ReLU, BN. It also has three fully connected layers and one convolutional layer. ReLU activation is function is used in first two fully connected layers and sigmoid function is used by third layer. Size of the filter is 3×3× 3. Filter number of convolutional layer corresponds to 256, 128, 64, 32 and fully connected layer has 1, 128 and 512 nodes.

Auto-Context Model (ACM) for Refinement:

Inside patch, context information available to train every training sample is limited because it is patch based. Network's modelling capacity is affected by this. ACM is used for enlarging the context in training stage. Semantic segmentation uses this commonly. Iteratively, various classifiers are trained. Previous classifier's output probability map and original image features are used to train the classifiers. Additional information of context is given by previous classifier output. This can be used by subsequent classifiers. For every classifier, input are processed one by one during test time. Initial input are concatenated with probability. Regression tasks based on deep learning can also be applied with ACM. Generated results are refined iteratively by adapting ACM. By this way, GAN is made aware about context.

Various GANs are trained iteratively. Form source and target patches inputs are taken. Second channel is concatenated with these patches with source patch. Next GAN are trained using both of this inputs. Figure 5 shows the illustration of this scheme. ACM uses same architectures of GANs. It is shown in figure 2.

Generator input are different between these two architectures. Synthetic target patch and source MRI patch are concatenated by this. In refinement based on ACM, same size of input patch is maintained. From entirely estimated previous target image, extract the context information. Information which are not in initial input image patch are encoded.

3 Experiments and Results

In two tasks, proposed model is tested using three datasets. From corresponding MRI data, CT images are estimated from brain and pelvic dataset and in second case, from 3T MRI data, 7T MRI data is estimated. Separately, results of experimentation for two different tasks are described.

3.1 PSNR performance comparison

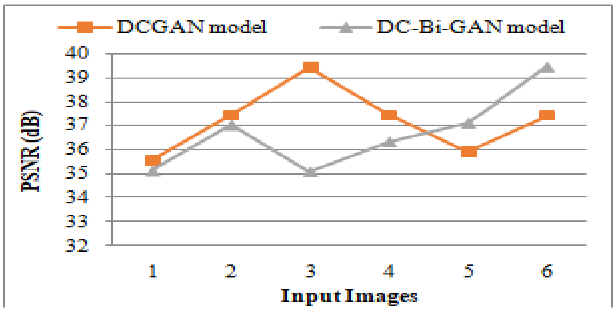

Fig.3. PSNR performance comparison

Fig.3 shows that the PSNR comparison results between Exiting DCGAN Based Method and Proposed DC-Bi-GAN based Method. The proposed method has high value of PSNR. From results, it is well know that proposed method obtain high PSNR indicating the good lung nodule detection. Because, the proposed scheme is based on excellent feature extraction and DC-Bi-GAN based concept is enhancing the learning efficiency. When comparing the PSNR rate among the existing methods at the same image size are providing fewer rates which indicates the proposed work can give better synthesis results than the existing method.

3.2 MSE performance comparison

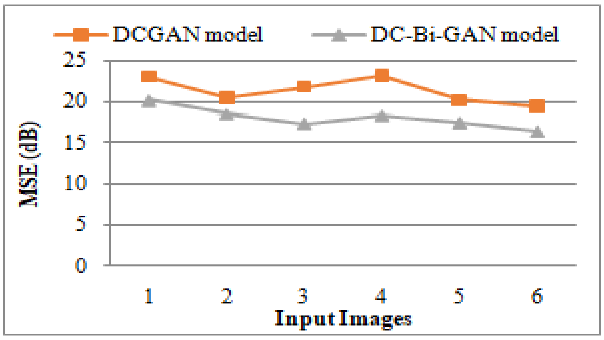

Fig.4. MSE performance comparison

Fig.4 shows that the MSE comparison results between Exiting DCGAN Based Method and Proposed DC-Bi-

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GAN based Method. The proposed method has low value of MSE. From results, it is well know that proposed method obtain less error value indicating the good detection rate. Because, the proposed scheme is having the effective image enhancement stage which reduce the noises. When comparing the PSNR rate among the existing methods at the same image size, providing high error rate which shows the proposed work can give better detection results than the existing method.

3.3 SSIM performance comparison

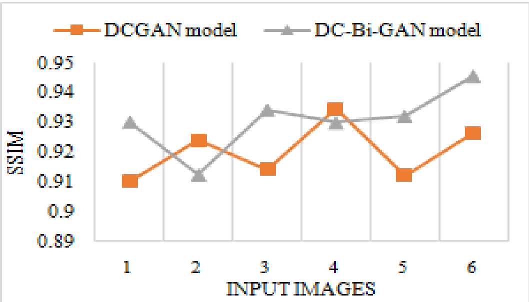

Fig.5. SSIM performance comparison

Fig.5 shows that the SSIM comparison results between exiting DCGAN based method and proposed DC-Bi-GAN based Method. From figure, proposed method can obtain high SSIM when compared to existing methods. It is an effective way of getting the lung nodule accurately with the high SSIM rate of 0.9456 at the image size is 6. When comparing the SSIM among the existing methods at the same image size of 6, providing less rate. Through the results, it can be seen that the proposed work is much better than the existing method.

3.4 Execution Time performance comparison

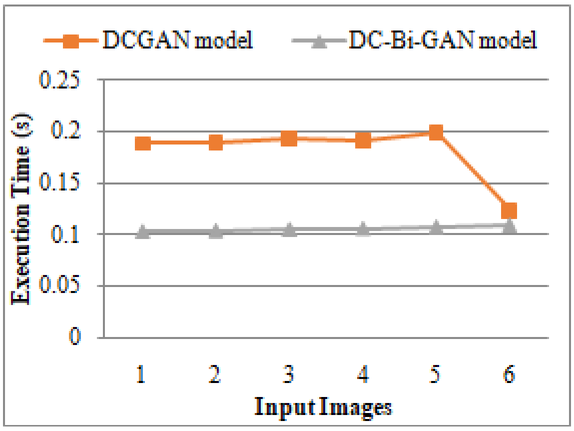

Fig.6. Execution Time performance comparison

Fig.6 shows that the execution time comparison results between exiting DCGAN based method and proposed DC-Bi-GAN based Method. From figure, proposed method can have less execution time when compared to existing methods. It is an effective way of getting the lung nodule accurately with the less execution time of 0.1096s at the image size is 6. When comparing the execution time results among the existing, all are providing high rate. Through the results, it can be seen that the proposed work is much better than the existing method.

3.5 Detection Accuracy

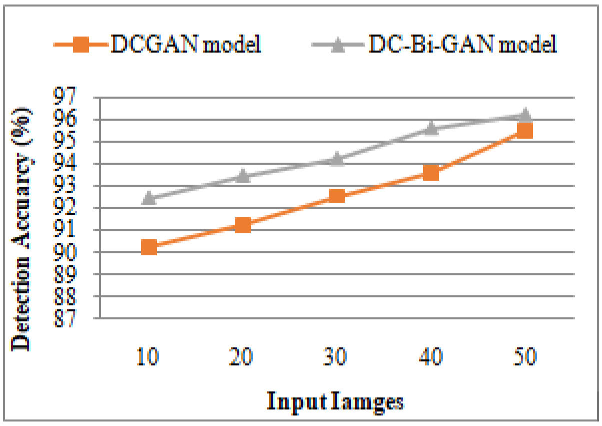

Fig.7. Detection Accuracy Vs No. of Images

Fig.7 shows combined detection accuracy of Exiting DCGAN based method and proposed DC-Bi-GAN based method under number of images. It is observed that the detection accuracy of proposed method is greater than existing scheme. From figure, it is observed that when the number of images increases, the average DA reduces in existing method. When proposed method is implemented, the average detection accuracy of proposed method and existing method are 96.25%, and 95.47% respectively. The reason is that; the genetic algorithm with DC-Bi-GAN will improve the rib suppression and nodule detection with an effective manner using deep convolutional network.

4 Conclusion and future work

From source images, target images are estimated by proposing supervised deep convolutional model through adversariallearning in this research. With genetic algorithm, images are estimated from various modality classes. Generated target image is enhanced by introducing special loss function. Long term residual connection is established by extending residual learning unit. This is used to train the network in an easy manner. ACM is used to enhance the performance iteratively. During training process, effectively enlarge the Bi-GAN context. This makes the awareness about context. On two tasks, proposed model is validated. From MRI data CT data is predicted and 7T MRI is formed from 3T MRI. In all dataset and task, proposed model shows superior performance than the existing models. Different medical images can be synthesized by using proposed method as indicated by results of experimentation.

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