International Journal of Innovative Research in Science and Engineering
Volume 08, Issue 06, 2022
www.ijirse.com
ISSN: 2454-9665

PET IMAGE DENOISING USING DEEP IMAGE PRIOR

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ABSTRACT

PET (positron emission tomography) is a radioactive based nuclear medical imaging, which helps in observing the metabolism of the cells and to diagnose the diseases. The quantitative accuracy of positron emission tomography (PET) is affected by several factors, including the intrinsic resolution of the imaging system and inherently noisy data, which result in a low signal-to-noise ratio (SNR) of PET image.To address this problem, we proposed a novel deep learning denoising framework aiming to enhance the accuracy of dynamic PET images via using of deep image prior (DIP) combined with Regularization by Denoising. The network structure is based on encoder-decoder architecture and uses skip connections to combine hierarchical features to generate the estimated image. In recent years, deep neural networks have shown great potential in image science, such as image restoration, segmentation, object detection, and image analysis, which show better performance than conventional state-of-the-art methods when large amounts of data sets are available. Recently, it has been gradually applied to medical imaging using convolutional neural networks.

Keywords: Positron Emission Tomography (PET), Deep Image Prior (DIP), Convolutional Neural Networks (CNN)

INTRODUCTION

Positron emission tomography (PET) is a type of nuclear medicine procedure that measures metabolic activity of the cells of body tissues. PET is actually a combination of nuclear medicine and biochemical analysis. Used mostly in patients with brain or heart conditions and cancer, PET helps to visualize the biochemical changes taking place in the body, such as the metabolism (the process by which cells change food into energy after food is digested and absorbed into the blood) of the heart muscle.

PET differs from other nuclear medicine examinations in that PET detects metabolism within body tissues, whereas other types of nuclear medicine examinations detect the amount of a radioactive substance collected in body tissue in a certain location to examine the tissue's function. A PET scan is an effective way to help identify a variety of conditions, including cancer, heart disease and brain disorders. Your doctor can use this information to help diagnose, monitor or treat your condition. Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications.

Digital image is noise due to distortion caused by poor quality image acquisition, images observed in a noisy environment or noise inherent in communication channels. There exists number of noise models caused by various reasons. Few noise models are Uniform, Gaussian, Salt and Pepper, andRayleighetc.PET image in this

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paper; we develop a novel deep learning denoising framework aiming to enhance the quantitative accuracy of dynamic PET images via introduction of deep image prior. The network input is not only random noise but other prior images. In this work, the static is used as the network input.

LITERATURE REVIEW

Positron emission tomography (PET) is a nuclear medical imaging modality enabling quantitative measurements of biomolecular mechanisms by radioactive tracers in vivo. However, the quantitative accuracy of PET is affected by several factors, including the intrinsic resolution of the imaging system and inherently noisy data, which result in low signal-to-noise ratio (SNR) of PET image [1]. Therefore, it is essential to improve the quantitative accuracy of PET images. Various pre- and post-reconstruction algorithms have been developed by exploiting local statistics, spatiotemporal correlation, or prior anatomical information for PET image enhancement [2]-[4].

The pre-processing method is carried out in PET sinogram to improve the estimation of physical parameters by using the spatiotemporal correlation in dynamic PET scans[5],[6]. For post processing algorithms, conventional Gaussian filtering (GF) has been applied for PET image enhancement in clinic. Other post-processing algorithms, such as non-local mean (NLM) [7],wavelet [8], HYPR processing [9], guided image filtering [10],bilateral filtering and kinetics-induced block matching and 5Dfiltering (KIBM5D) [10] have been proposed, and outperform conventional Gaussian filtering in terms of reducing image noise as well as preserving more image structure details

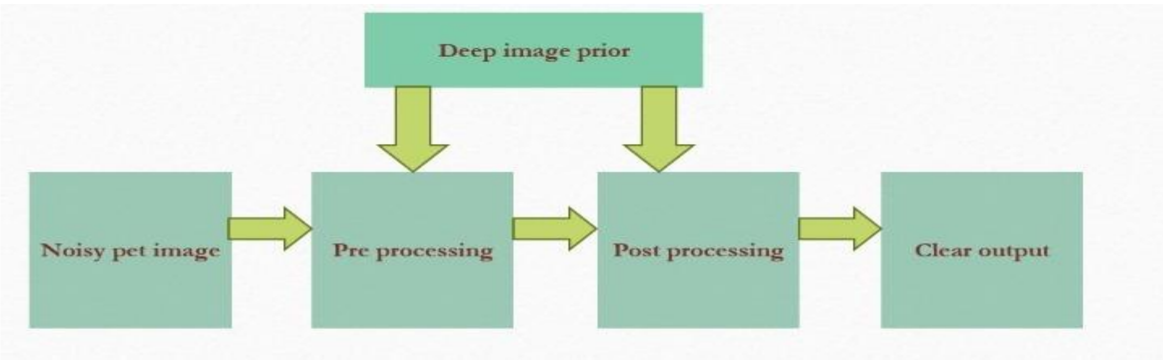

Fig.1: block diagram showing the procedure of denoising the noisy PET images

In our denoising framework, the original image (e.g., noisy image) is set as a target image, and mean squared error (MSE)is used to measure the difference between the label and the network output. The network structure is based on encoder-decoder architecture and skip connections to combine hierarchical features for generating the estimated image Recently, the deep image prior (DIP) [7] shows that the structure of a generator network is sufficient to capture a great deal of low-level image statistics prior to any learning without pre-training.

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EXISTING METHODS

Gaussian filters

The Gaussian blur is a type of image processing that applies a filter on an image. This filter takes the surrounding pixels (the number of which is determined by the size of the filter) and returns a single number calculated with a weighted average based on the normal distribution.

Block matching and 3d filtering (BM3D)

Block-matching and 3D filtering (BM3D) is a 3-D block-matching algorithm used primarily for noise reduction in images. It is one of the expansions of the non-local means methodology. There are two cascades in BM3D: a hard-thresholding and a Wiener filter stage, both involving the following parts: grouping, collaborative filtering, and aggregation.

Non-Local Mean (NLM)

Non-local means is an algorithm in image processing for image denoising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. These results in much greater post-filtering clarity, and less loss of detail in the image compared with local mean algorithms.

Some of the conventional noise filters are gaussian noise filters, low pass filters and high pass filters, But the problem with those filters is those that they can filter the noise only to some extent but in our PET images we have noise to greater extent than that of CT and MRI. So, we seek the help of deep image prior to solve this issue.

PROPOSED METHOD

Auto Encoder:

Auto encoder is an unsupervised artificial neural network that is trained to copy its input to output. Let’s consider that we are given an image, an auto encoder will first encode the image into a lower-dimensional representation, then decodes the representation back to the image.

With appropriate dimensionality and sparsity constraints, auto encoders can learn data projections that are far more interesting than PCA or other basic techniques.

Auto encoders are only able to compress data similar to what they have been trained on. They are also lossy in nature which means that the output will be degraded compared to the original input.

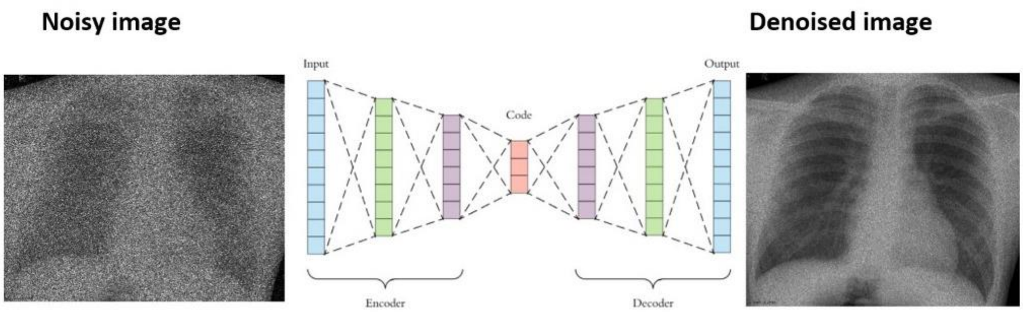


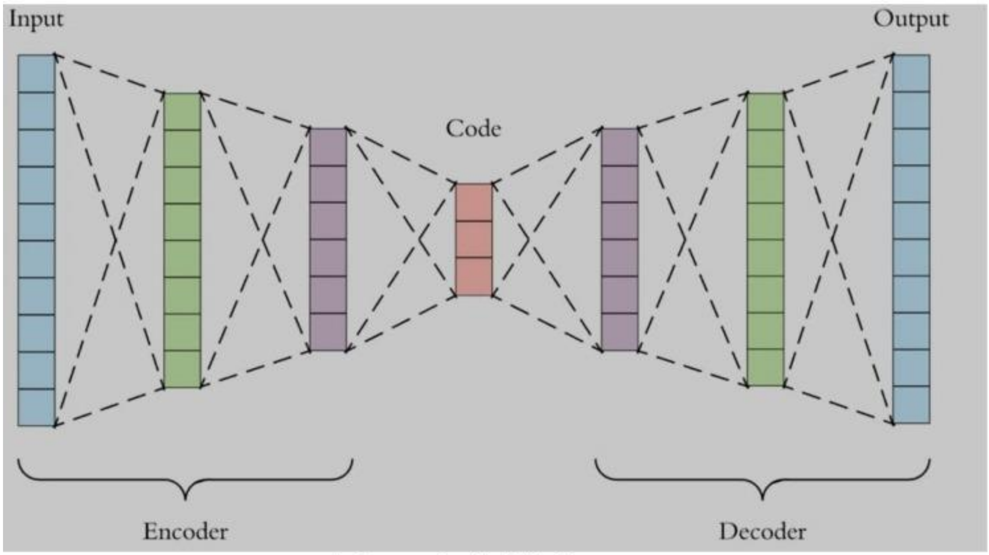
Fig.2: denoising of the medical image with the proposed method

Architecture

There are mainly 3 parts in auto encoders

1. Encoder: In this part of the architecture the model compresses the input data to represent the compressed data in a reduced dimension.
2. Code: Also known as Bottleneck this part of the architecture represents the compressed data that is going to be fed to the decoder.
3. Decoder: This part reconstructs the encoded data as close to the input data as possible. The output from the decoder is a lossy reconstruction of the original data.

The goal of an autoencoder is to get an output that is identical to the input. The dimensionality of the input and output is similar as obviously the goal is to get the output as identical to the input we can get.
They are trained similarly to ANNs via back propagation.



Autoencoder Architecture

RESULTS

Simulation is performed in jupyter notebook, with python 3 (ipykernel) and a number of predefined libraries and user defined functions have been used. We have developed a convolutional auto encoder which has encoder decoder-based architecture. Initially we have to add some noise to the training positron tomography images and then tarin the auto encoder with the training images by running a 100 epoch then we denoise the images with the help of the auto encoder. Then the result of the auto encoder is compared with the other conventional or existing methods.

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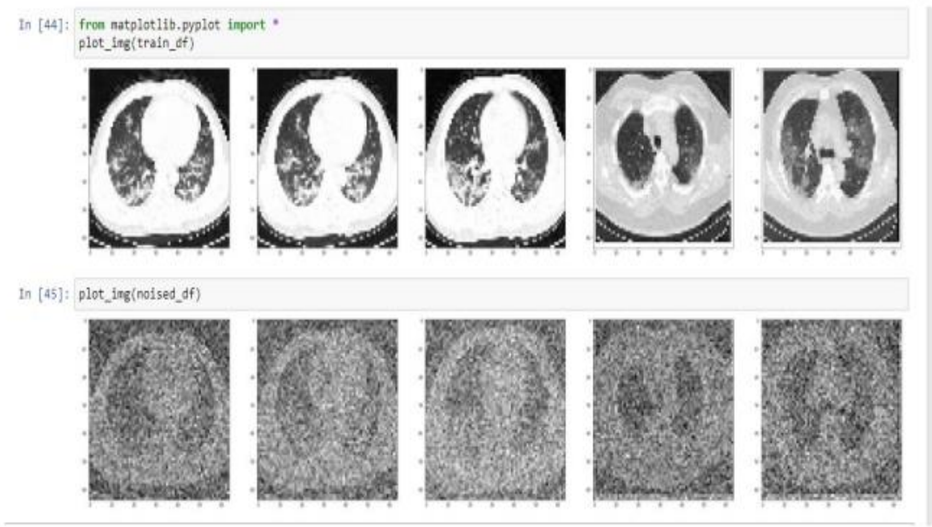


Fig.3: PET training images and images with some noise added to them.

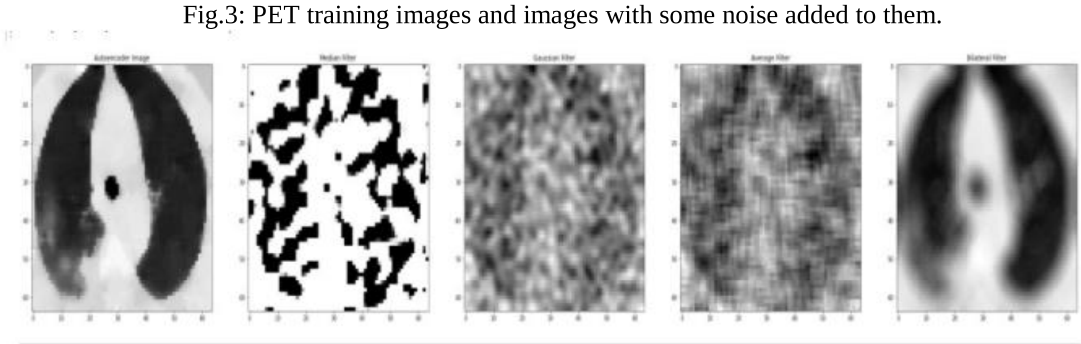
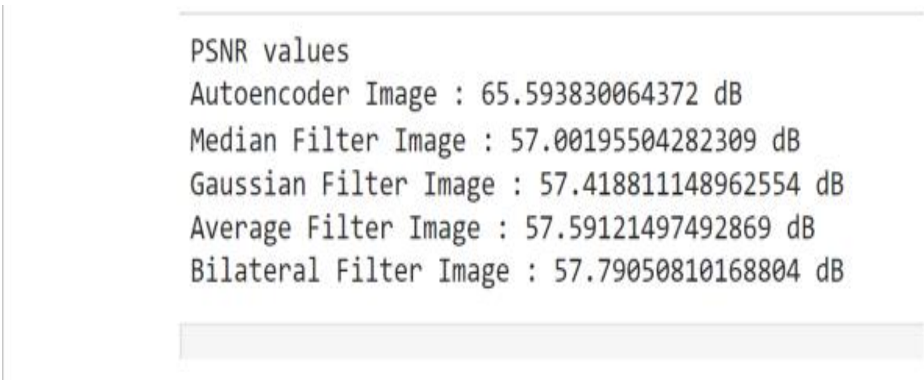


Fig.4: comparing the denoised images of auto encoder, median filter, gaussian filter, average filter and bilateral filter.



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PSNR values
Autoencoder Image : 65.593830064372 dB
Median Filter Image : 57.00195504282309 dB
Gaussian Filter Image : 57.418811148962554 dB
Average Filter Image : 57.59121497492869 dB
Bilateral Filter Image : 57.79050810168804 dB
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Fig.5: Final output showing PSNR (Peak Signal to Noise Ratio) of all denoising techniques.

CONCLUSION

In this work, we developed a novel deep learning denoising framework aiming to enhance quantitative accuracy of dynamic PET images via introduction of deep image prior combined with Regularization by Denoising that is by using a convolutional auto encoder. The proposed method avoids the need of high-quality noiseless images, and random noise or prior images can be used as the network input. Furthermore, the method combines the pre-training networks and image denoising process by constructing a constrained optimization problem and alleviates the necessity of stopping early for DIP method. Both simulation and patient data experiments show that the proposed method outperforms the conventional gaussian filters, median filters, average filters, bilateral filters method in visual as well as quantitative improvements. Future work will focus on better network architecture and increasing the speed of processing in order to make the method more practical and effective in clinical data sets.

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