FAST AND FLEXIBLE DENOISING NETWORK USING NOISE BASED PREDEFINED LAYERS BASED ON IMAGE DENOISING: REVIEW

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Abstract - *Any information system emits, by conduction or radiation, compromising signals likely to be intercepted by an attacker. Those leakage signals usually have low signal-to-noise ratio and the security information of systems depends on the capacity of an attacker to denoise them. Denoising is a major topic in signal processing, currently revolutionized by deep learning methods. In particular, the scope of image denoising is large and ranges from classical and low footprint techniques to computationally intensive deep learning techniques. In Deep learning algorithms pre-trained image denoising convolutional neural network model is used that typically run onto energy costly computers using Graphics Processing Units (GPUs) and are currently hardly available in an embedded context. As the number of digital images taken every day, the demand for more accurate and visually pleasing images is increasing. However, the images captured by modern cameras are degraded by noise, which leads to worst visual image quality. Therefore, it is required to reduce noise without losing image features such as edges, corners, and other sharp structures. In our approach we adapted fast and flexible denoising convolutional neural network, namely FFDNet which works on downsampled sub images to achieve a good tradeoff between inference speed and denoising performance. Here is an attempt of understanding and reviewing of different image denoising methodologies.*

Key Words: Image denoising, convolutional neural networks, Gaussian noise, salt and pepper noise, spatially variant noise.

1. INTRODUCTION

Image denoising is used to remove additive noise while retaining the signal features. Generally datasets collected by image sensors are contaminated by noise. Data of interest can be corrupted because of imperfect instruments, problems with data acquisition process, and interfering natural phenomena. Thus noise reduction is an important technology in image analysis. For image denoising different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images.

In order to handle practical image denoising problems, a flexible image denoiser is expected to have desirable properties such as; must be able to perform denoising using single model, efficient, effective and user friendly, it can handle spatially variant noise. When the noise level is known it is easy for denoiser to recover the clean image. When the noise level is unknown, the denoiser should allow the user to adaptively control the trade-off between noise reduction and detail preservation.

In this paper we adapted a fast and flexible denoising convolutional neural network, namely FFDNet which is able to deal with noise on different levels by taking a tunable noise level map as input. FFDNet works on downsampled sub-images which largely accelerates training and testing speed. FFDNet has several desirable properties such as the ability to handle a wide range of noise levels with a single network, the ability to remove spatially variant noise by specifying a non-uniform noise level map, and faster speed than benchmark BM3D [16].

2. IMAGE DENOISING METHODOLOGIES

In this section, we briefly review on Image Denoising Methodologies

2.1 Spatial filtering

A large number of spatial filtering has been applied to image denoising, which can be further classified into two types. Those are linear filter and non-linear filter. Linear filters were adopted to remove noise in the spatial domain, but they fail to preserve image texture. Mean filter has been adopted for Gaussian noise reduction; however it can over smooth image with high noise

[1]. To overcome this drawback, Wiener filtering [2][3] has further been employed, but it can also easily blur sharp edges. In order to overcome the drawbacks of all these filters non-linear filters such as median filtering [4][5] and weighted median filtering [6] have been adopted to suppress the noise without any identification. Spatial filtering makes use of low pass filtering on pixel groups by indicating that the noise occupies a higher region of the frequency spectrum. Spatial filters eliminate noise to a reasonable extent but at the cost of image blurring, which in turns loses sharp edges.

2.2 Transform Domain Filtering

Transform domain filtering methods first transform the given noisy image to another domain and then they apply a denoising procedure on the transformed image according to their characteristics of the image and its noise. Depending upon the transform function transform domain filtering methods can be divided into two methods, they are: data adaptive and non-data adaptive [13].

2.2.1 Data adaptive transform

In data adaptive transform method Independent Component Analysis (ICA) [7] [8] and PCA [9] [10] functions are adopted as the transform tools on the given noisy images. The ICA methods have been successfully used for denoising non-Gaussian data. One advantage of using ICA is its assumption signal to be non-Gaussian which helps to denoise images with non-Gaussian as well as Gaussian distribution. Disadvantage of ICA based methods as compared to wavelet based methods are the computational cost because it uses a sliding window and it requires sample of noise free data.

2.2.2 Non-data adaptive transform

Non-data adaptive transform method can be further classified into two domains, namely spatial frequency domain and wavelet domain. Spatial frequency domain method uses low pass filtering by designing a frequency domain filter that passes all frequencies lower than and attenuates all frequencies higher than a cut-off frequency [4][2]. After transforming through low pass filtering, as a result the image information spreads in the low frequency domain and noise spreads in the high frequency domain. Thus it is possible to remove noise by selecting specific transform function such as Fourier transform function features and transforming them back to the image domain [11]. But these methods have some drawbacks such as time consuming and depend on the cut-off frequency and filter function behavior. Whereas wavelet transform function [12] decomposes the input data into a scale space representation. It has been proved that wavelet can successfully remove noise while preserving the image characteristics regardless of its frequency content.

2.3 BM3D and WNNM

Generally image denoising methods can be grouped into two major categories, those are model based methods and discriminative learning based methods. BM3D [14] and WNNM [15] are comes under model based methods. BM3D is nothing but a two stage non-locally collaborative filtering method in the transform domain. In this method similar patches are stacked into 3D groups by block matching, and the 3D groups are transformed into the wavelet domain. After performing inverse transform of coefficients, all estimated fatches are combined to reconstruct the whole image. However when the noise goes on increases gradually, the denoising performance of BM3D decreases greatly.

The traditional Weighted Nuclear Norm Minimization (WNNM) has excellent performance for the removal of non-sparse noise such as Gaussian noise, but attains bad performance for the removing of salt and pepper noise and mixed noise of Gaussian noise. BM3D and WNNM are flexible in handling denoising problems with various noise levels, but they suffer from several drawbacks such as time consuming and cannot be directly used to remove spatially variant noise. Moreover, model based methods usually employ hand crafted image priors, which may not be strong enough to characterize complex image structures.

2.4 CNN based denoising methods

The variational denoising methods discussed above are belonging to model based denosing scheme, which find optimal solutions to reconstruct the denoised image. However, such methods usually involve time consuming iterative interference. On the contrary, the CNN based methods attempt to learn a mapping function by optimizing a loss function on training set that contains degraded-clean image priors. Because of its flexible connection of the deep network architecture and strong learning ability, deep learning techniques have become most effective to address these image denoising problems.

3. COMPARISON

AUTHORS AND YEAR	TITLE	CONTRIBUTION
Yushu Zhang, Hongo Lin, Haitao MA. 2019	A Patch Based Denoising Method Using Deep Covolutional Neural Network for Seismic Image	In this approach, the PDCNN method is adopted to suppress the spatiotemporally variant seismic random noise. Where its critical point lies in patches clustering and joint denoising with multiple CNN models to handle all the noise levels existing in the spatiotemporally variant random noise. PDCNN automatically selects the CNN models for removing the seismic random noise with spatiotemporally variant levels [16].
Fumio Hashimoto, Hiroyuki Ohba, Kibo Ote, Atsushi Teramoto, Hideo Tsukada. 2019	Dynamic PET Image Denoising Using Deep Convolutional Neural Networks Without Prior Training Datasets	There are large number of deep learning methods are available based on CNNs have been investigated for PET imaging. However, these methods are difficult to apply in a clinical setting if the case is unknown, not included in the training data sets. So in order to overcome this problem they have adopted Deep Image Prior (DIP) method, which has the ability to solve inverse problems such as denoising without pre-training and do not require the preparation of training data sets. In this approach they proposed dynamic PET image denoising using DIP method, with the PET data itself is used to reduce the stastical image noise [17].
Yanling Wang, Yanling Shao, Quan Zhang, Yi Liu, Yan Chen, Wenbin Chen, Zhiguo Gui. 2017	Noise Removal of Low Dose-CT Images Using Modified Smooth Patch Ordering	In this paper a post processing approach namely modified smooth patch ordering (MSPO), for LDCT image have been used. The proposed approach is based on modified NLM algorithm and smooth ordering of the pixels in LDCT image. In the MSPO method, the NLM algorithm is modified by replacing the Leclerc robust function with the modified bisquare robust function, to serve as weight function for the estimate of each pixel value. Then the modified NLM algorithm is combined with smooth ordering of pixels patch classification, and subimage averaging scheme to denoise LDCT image [19].
Gabriela Ghimpeteanu, Thomas Batard, Marcelo Bertalmio, Stacey Levine. 2016	A Decomposition Framework for Image Denoising Algorithm	The strategy they developed in this paper is to denoise the components of the image which is to be processed in a moving frame that encodes directions of gradients and level lines. For this purpose they have developed VTV based denoising method, NLM and BM3D algorithms on both gray level and color images tested over the Kodak database showed that this strategy systematically improves the denoising method in terms of PSNR and SSIM metrics [18].

4. FUNDAMENTAL SEQUENCE INVOLVED IN IMAGE PROCESSING SYSTEM

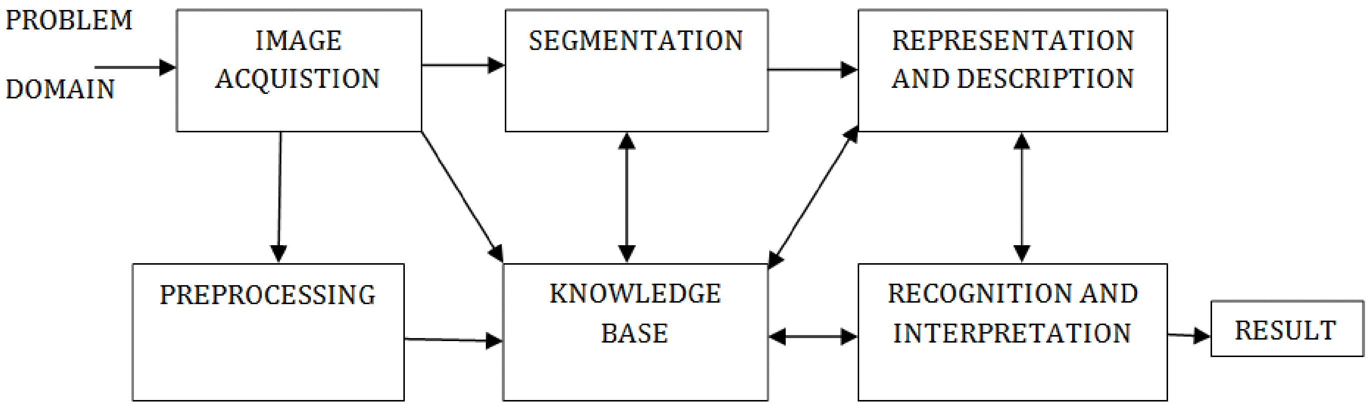

Fig1. Block diagram of fundamental sequence involved in an image processing system

As shown in the above diagram, the first step in the processing of an image is image acquisition by an imaging sensor in conjunction with a digitizer to digitize the image. The next step is the preprocessing step which improves the image quality and sends this improved image as input to the other processes. Preprocessing is the process which suppresses unwanted distortions or enhances some image features important for further processing and it does not increase information content. Segmentation is the process of portioning an image into parts or regions. Segmentation involves converting an image into a collection of regions of pixels that are represented by a mask or labeled image. By dividing an image into segments we can process the only important segments of the image instead of processing the entire image and provides raw pixel data as output. The output of the segmentation process that is raw pixel data are transformed into a form useful for subsequent processing by the representation process, whereas description deals with extracting features that are basic in differentiating one class of objects from another. Based on the information provided by the descriptor Recognition assigns a label to an object. Interpretation is a higher level process which uses combinations of the methods, namely sensing, preprocessing, segmentation, description and recognition. The operation of each processing module is guided by knowledge base guide and it also controls the interaction between the modules.

5. CONCLUSION

The purpose of this paper is to present a survey of image denoising approaches. As images are very important in each and every field so, Image Denoising is an important pre-processing task before further processing of image like segmentation, feature extraction, texture analysis etc. In this review we studied different image denoising methodologies. As compared to model based methods such as BM3D and WNNM are flexible in handling denoising problems with various levels of noise, but they suffer from several drawbacks, such as time consuming, and cannot be directly used to remove spatially variant noise. Whereas MLP takes vector as input and CNN takes tensor as input, so that CNN can understand the spatial relation between the pixels of images thus for complicated images CNN will perform better than MLP. FFDNet spends the same time for processing both grayscale and color images. In case of multi-thread implementation FFDNet is about three times faster than DnCNN and BM3D on CPU, and much faster than DnCNN ON GPU. Even with the single-thread implementation, FFDNet is also faster than BM3D. Taking denoising performance and flexibility into consideration, FFDNet is very competitive for practical applications and provides a practical solution to CNN denoising applications. Based on the performance of all techniques mentioned above it can be concluded that the performance of the convolutional neural network is good as far as the best method for denoising an image.

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