BILATERAL FILTERING ASSOCIATED WITH BILATERAL NEURAL NETWORKS BASED AUTOMATIC NOISE REMOVAL SYSTEM FOR BRAIN IMAGES

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ABSTRACT

Today's the medical image processing represent important role in the medical field. Image processing is an Electronic Domain wherein image is divided into small unit called pixel, and then various operation has been carried out. Image filtering, these days, has become an active research area in the domain of Image processing. Noise removal in MRI (Magnetic Resonance Image) scan image is important and essential for a wide variety of subsequent processing applications. Among the abundant denoising algorithms, the bilateral filter has been widely used in many image preprocessing procedures. However, it requires laborious tuning of parameters to obtain optimal filtering results, which is tedious and time-consuming. In this paper, we propose an automatic noise removal system based on the bilateral filter with bilateral neural network for different brain images. And we use bilateral neural networks for the use of high dimensional sparse data.

Keywords: image processing, magnetic resonance image, denoising, bilateral filter, bilateral neural network.

1. INTRODUCTION

The past decade had witnessed a rapid and multi faced increase in the applications of image processing. There are plenty of researches are done on medical imaging system, in this field brain disease extraction in Magnetic Resource Imaging (MRI) is a standard process. In medical imaging, many image analysis applications developed for medical diagnosis involves segmentation of tissues and structures. In today's digital era, capturing, storing and analysis of medical image had been digitized. Detailed interpretation of medical image is a challenge due to the constraint of time and accuracy. The challenge gets more demanding especially in regions with abnormal color and shape which needs to be identified and interpreted by radiologists for future studies. The key task in designing such image processing and computer vision applications is the accurate segmentation of medical images. Image segmentation is the process of partitioning different regions of the image based on different criteria. Surgical planning, post-surgical assessment, abnormality detection, and many other medical applications require medical image segmentation. The main challenges in medical image segmentation are unknown and irregular noise, in homogeneity, poor contrast and weak boundaries. MRI and other medical images contain complicated anatomical structures that require precise and most accurate segmentation for clinical diagnosis. The detection of brain disease is a very challenging task, in which special care is taken for image segmentation. A particular part of body is scanned in the discussed applications of the image analysis and techniques such as MRI, CT scan, and X rays. MRI technique helps in collecting the best information about the human soft tissue anatomy.

Over the decades, Gaussian filters have been widely used in many MR image processing applications for its simplicity [11]. Although the Gaussian filter smoothes noise quite efficiently edges are blurred significantly. To preserve the sharpness, the bilateral filter [12] has been proposed that performed effectively in MR image noise suppression and it has been the object of further studies [13]. However, the bilateral filter requires laborious tuning of parameters to obtain optimal filtering results, which is tedious and time-consuming. Automation of these parameters through artificial intelligence techniques will be highly beneficial. To address this problem, this paper proposes to automate the bilateral filter based on an artificial neural network.

1.1 Types of noise

a) Gaussian noise

Additive noise is one of the most common problems in image processing. Even a high resolution photo is bound to have some noise in it. For a high-resolution photo a simple box blur may be sufficient, because even a tiny features like eyelashes or cloth texture will be represented by a large group of pixels. Unfortunately, this is not the case with video where real-time noise reduction is still a subject of many researches.

b) Salt and pepper noise

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. An effective noise reduction method for this type of noise involves the usage of a median filter or a contra harmonic mean filter. Salt and pepper noise creeps into images in situations where a quick transient, such as faulty switching, takes place.

c) Speckle noise

The speckle noise is commonly found in the ultrasound medical images. It is a granular noise that

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inherently exists in and degrades the quality of the Active Radar and Synthetic Aperture Radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image processing element. It increases the mean grey level of a local area. Speckle noise in SAR is generally more serious, causing difficulties for image interpretation. It is caused by coherent processing of backscattered signals from multiple distributed targets. In SAR oceanography, for example, speckle noise is caused by signals from elementary scatterers, the gravity-capillary ripples, and manifests as a pedestal image, beneath the image of the sea waves.

1.2 Basics of bilateral neural network

Feedforward neural network or Multilayer Perceptron with multiple hidden layers in artificial neural networks is usually known as Deep Neural Networks (DNNs). Convolutional Neural Networks (CNN) is one kind of feedforward neural network. In 1960s, when Hubel and Wiesel researched the neurons used for local sensitive orientation-selective in the cat's visual system, they found the special network structure can effectively reduce the complexity of Feedback Neural Networks and then proposed Convolution Neural Network. CNN is an efficient recognition algorithm which is widely used in pattern recognition and image processing. It has many features such as simple structure, less training parameters and adaptability. It has become a hot topic in voice analysis and image recognition. Its weight shared network structure makes it more similar to biological neural networks. It reduces the complexity of the network model and the number of weights. Generally, the structure of CNN includes two layers one is feature extraction layer, the input of each neuron is connected to the local receptive fields of the previous layer, and extracts the local feature. Once the local feature is extracted, the positional relationship between it and other features also will be determined. The other is feature map layer; each computing layer of the network is composed of a plurality of feature map. Every feature map is a plane, the weight of the neurons in the plane are equal. The structure of feature map uses the sigmoid function as activation function of the convolution network, which makes the feature map have shift invariance. Besides, since the neurons in the same mapping plane share weight, the number of free parameters of the network is reduced. Each convolution layer in the convolution neural network is followed by a computing layer which is used to calculate the local average and the second extract, this unique two feature extraction structure reduces the resolution.

2. RELATED WORK

Marvasti *et al*, [1] proposed a new method based on the wavelet transform. In this method an improved TNN were introduced by utilizing a new class of smooth non-linear thresholding functions as the activation function. This approach introduced best threshold in the sense of minimum MSE mean square error. TNN obtained thresholds were employed using a cycle spinning based technique to reduce the image artifacts. This method outperforms other established wavelet de-noising techniques in terms of PSNR and visual quality.

Rehman Amjad *et al*, [2] presented a novel approach based on the Cellular neural networks (CNN) to denoise an image also in presence of high noise. Image De-noising was come up with a regression problem between the noise and signals which is solved by using CNN. The noises are detected with surrounding information and removed. The proposed algorithm exhibited promising results from qualitative and quantitative point of view. Experimental results of the proposed algorithm exhibit high performance in PSNR and visual effects in color image even in the presence of high ratio of the noise

Santhanam *et al*, [3] proposed an Artificial Neural Network for image classification that followed by the suitable filter classification for particular type of noise which removed. In this method the Multilayer perception (MLP), Back propagation neural network(BPNN), Probabilistic Neural network(PNN) are used to classify the noise in an image as non Gaussian white noise, Gaussian noise and salt and pepper noise after this noise inputs are provided for MLP, BPNN, and PNN which identifies the suitable filters for the noise removal.

Al-SobouYazeed [4] presented neural network as a noise reduction efficient and robust tool where this research BPNN is used as learning algorithm and this approach includes using both mean and median statically functions for calculating the output pixels of the NN. It uses a part of degraded image pixels to generate the system training pattern. Output of the proposed approach provided a good image de-noising performance which exhibits promising results of the degraded noisy image in the name of PSNR, MSE and visual test.

FarhadEsfahani *et al,* [5] proposed Median Filter in conjunction with Linear Filter to remove Impulsive noise from measurement data which had good minimization error but the computation time was very high. Harish Kundra et.al, [6] proposed denoised Salt and Pepper noise from image of Taj Mahal in 15 sec using 8-neighborhood method and also preserved the intricate features of the image. In similar way Dimitri Van De Ville *et al*, [7] removes Additive noise from Camera-man and Boat. This Filter was very feasible, fast, and simple and enabled fast hardware implementation. M. EminYüksel *et al*, [8] used same logic to remove Impulsive Noise from Baboon which also preserves image detail and texture. The filter was flexible and simple. M. EminYüksel *et al*, [9] introduced remarkable technique of Neuro-Fuzzy Sub Detector along with decision maker for removing Impulsive noise from the images of Baboon, Boats, cameraman and pentagon. This filter has reduced distortion effect due to noise removal operator and also reduced the blurring effect. M. EminYuksel *et al*, [10] modified their previous work by introducing Recursive Switching Median filter guided by Neuro-Fuzzy network which reduces Impulsive noise from Baboon, Blood, Boats, Bridge, Cameraman, Gold hill, Lena, Pentagon,

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Peppers and Rice. The filter preserved the detail of the image.

3. PROPOSED SYSTEM WORK

The proposed automatic bilateral filtering associated with the bilateral neural network framework consists of two major phases: training and testing, as shown in the Figure-1.

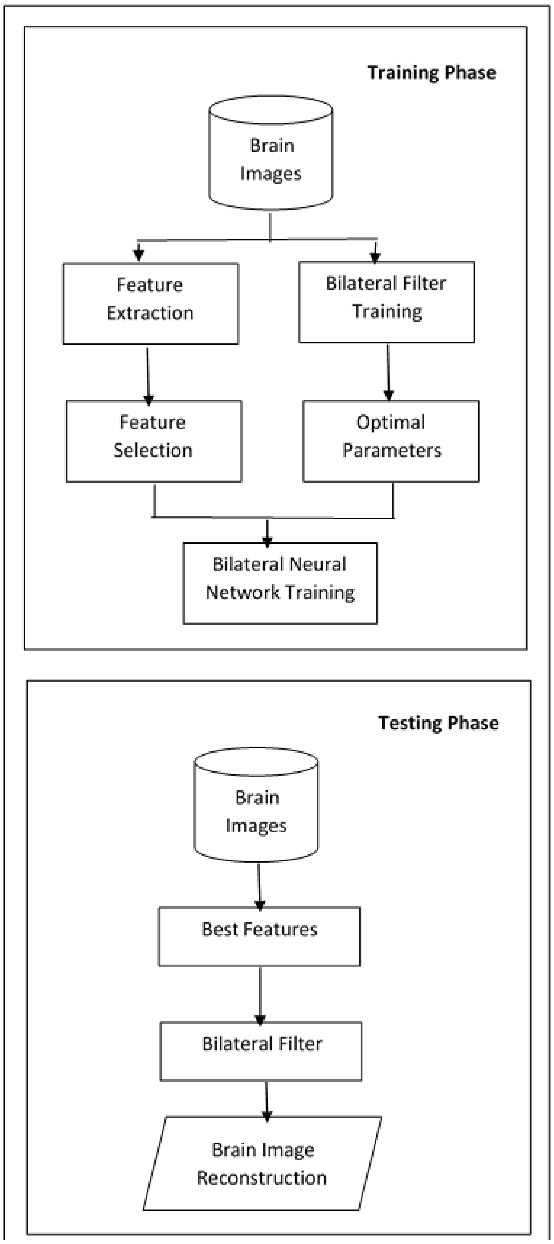

Figure-1. Proposed system model.

Our proposed System develop a novel framework for automatic noise removal of the given brain images using Bilateral Filter and Bilateral Neural Network. A new machine learning approach bilateral neural network is used where it contains two phases such as training and testing. Figure 1 shows the proposed system architecture to remove the noises of brain (medical) images. In that figure, initially the input brain images are taken for training process. Using bilateral filter, the image is preprocessed to remove artifacts or labels. Then, we use bilateral neural networks for the use of high dimensional sparse data. Finally, bilateral filter is useful for reconstructing images (i.e. Noises removed).

3.1 Preprocessing

The preprocessing mechanism, operators and techniques are used to perform initial processing improves the quality of brain image. Preprocessing is a stage where the requirements are usually noticeable and simple, like artifacts removal from images or image information elimination is not necessary for further process. The main aim of this process is to enhance the picture with high resolution and to classify the image for the next step by restricting the extra portions in the setting of real image. Firstly, the number of CT images of the brain tumor is collected from the healthcare organization. The images of brain tumor could be scanned by CT scan device. Some of the general techniques are used for removing the waste content like highlights, noise, and background from the image. This work exploits the bilateral filter for removing the noises from CT image. Bilateral filter which has been proved to be an efficient and effective method for noise reduction.

We have adopted the famous BrainWeb [14] image data of T1-weighted 1mm and 5mm MR image volumes with various levels of noise and intensity non-uniformity to evaluate the proposed system.

4. ALGORITHMS USED

4.1 Bilateral filtering

Bilateral filtering [11] is a non-linear filtering technique which can combine image information from both of the space domain and the feature domain in the filtering process. It can be represented by the equation 1

$$h(x) = \frac{1}{k(x)} \sum_{y} I(y) c(x,y) s(I(x), I(y)) \quad \ldots\ldots\ldots\ldots (1)$$

where,

I and h are the input and output images respectively,
x and y are pixel positions over the image grid,
c(x,y) and s(I(x),I(y)) measure the spatial and photometric affinity between pixel x and pixel y respectively, and

$$k(x) = \sum_{y} c(x,y) s(I(x), I(y)) \quad \ldots\ldots\ldots\ldots (2)$$

is the normalization factor at pixel x. The functions c(·) and s(·) are usually chosen as follows:

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$$c(x,y) = \exp\left(\frac{-\|x-y\|_2^2}{2\sigma_d^2}\right) \ldots\ldots\ldots (3)$$

$$s(u,v) = \exp\left(\frac{-\|u-v\|_2^2}{2\sigma_r^2}\right) \ldots\ldots\ldots (4)$$

The underlining idea of the bilateral filtering is to do the smoothing according to pixels not only close in the space domain, but close in the feature domain as well, thus the edge sharpness is preserved by avoiding the cross edge smoothing. Bilateral filtering is closely related to other edge preserving techniques such as nonlinear diffusion and adaptive smoothing [15].

4.2 Bilateral neural network

Probably the most promising opportunity for the generalized bilateral filter is its use in Convolutional Neural Networks. Since we are not restricted to the Gaussian case anymore, we can run several filters sequentially in the same way as filters are ordered in layers in typical spatial CNN (convolutional neural networks) architectures. Having the gradients available allows for end-to-end training with backpropagation, without the need for any change in CNN training protocols. We refer to the layers of bilateral filters as “bilateral convolution layers” (BCL). It can be either linear filters in a high dimensional space or a filter with an image adaptive receptive field. In the remainder we will refer to CNNs that include at least one bilateral convolutional layer as a bilateral neural network (BNN).

4.2.1 CNN architecture design

CNN algorithm need experience in architecture design, and need to debug unceasingly in the practical application, in order to obtain the most suitable for particular application architecture of CNN. Based on gray image as the input of 96×96, in the preprocess stage, turning it into 32 × 32 of the size of the image. Design depth of the layer 7 convolution model: input layer, convolution layer C1, sub sampling layer S1, convolution layer C2, sampling layer S2, hidden layer H and output layer F.

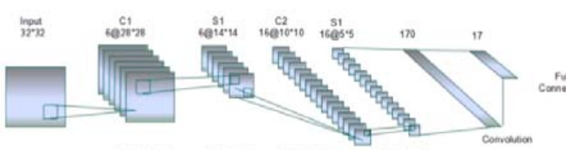

Figure-2. Architecture of CNN in training faces.

In view of the32 × 32input after preprocessing, there is a total of 17 different pictures. C1 layer for convolution, convolution layer adopts 6 convolution kernels, each the size of the convolution kernels is 5 × 5,can produce six feature map, each feature map contains (32-5 + 1) × (32-5 + 1) = 28 × 28 = 784 neurons. At this point, a total of 6 × (5 × 5 + 1) = 156 parameters to be trained.

S1 layer for sub sampling, contains six feature map, each feature map contains 14 * 14 = 196 neurons. the sub sampling window is 2 × 2 matrix, sub sampling step size is 1, so the S1 layer contains 6 × 196 × (2 × 2 + 1) = 5880 connections. Every feature map in the S1 layer contains a weights and bias, so a total of12parameters can be trained in S1 layer.

C2 is convolution layer, containing 16 feature graph, each feature graph contains (14-5 + 1) (14-5 + 1) = 100 neurons and adopts full connection, namely each characteristic figure used to belong to own 6 convolution kernels with six characteristics of the sample layer S1 convolution and figure. Each feature graph contains 6×5×5 = 150 weights and a bias. So, C2 layer contains a total of 16×(150+ 1)=150parameters to be trained.

S2 is sub sampling layer, containing 16 feature map, each feature map contains 5×5 neurons, S2 total containing 25×16 = 400 neurons. S2 on characteristic figure of sub sampling windowfor2×2, so there is 32 trainable S2 parameters.

As a whole connection layer, hidden layer H contains 170 neurons; each neuron is connected to 400 neurons on S2. So H layer contains 170× (400+1)=48120 parameters feature map.

Output layer F for all connections, including 17 neurons. A total of 17× (170 + 1) = 2907 parameters to be trained.

4.2.2 CNN algorithm

(i) Forward pass

Output of neuron of row k, column y in the lth convolution layer and kth feature pattern :

$$O_{x,y}^{(l,k)} = \tanh\Big(\sum_{t=0}^{f-1}\sum_{r=0}^{k_h}\sum_{c=0}^{k_w} W_{(r,c)}^{(k,t)} O_{(x+r,x+c)}^{(l-1,t)} + Bias^{(l,k)} \ldots\ldots\ldots (5)$$

Where,

f is the number of convolution cores in a feature pattern.

Output of neuron of row x, column y in the lth subsample layer and kth feature pattern:

$$O_{x,y}^{(l,k)} = \tanh\Big(W^{(k)}\sum_{r=0}^{S_h}\sum_{c=0}^{S_w} O_{(x\times S_h+r,\, y\times S_w+c)}^{(l-1,k)} + Bias^{(l,k)} \ldots\ldots\ldots (6)$$

The output of the jth neuron in lth hide layer H:

$$O_{(l,j)} = \tanh\Big(\sum_{k=0}^{s-1}\sum_{x=0}^{S_h}\sum_{y=0}^{S_w} W_{(x,y)}^{(j,k)} O_{(x,y)}^{(l-1,k)} + Bias^{(l,j)} \ldots\ldots\ldots (7)$$

Where,

S is the number of feature patterns in sample layer.

Output of the ith neuron lth output layer F

$$O_{(i,l)} = \tanh\left(\sum_{j=0}^{H} O_{(j-1,l)} W^{l}_{(i,l)} + Bias^{(i,l)}\right) \ldots\ldots\ldots\ldots (8)$$

5. CONCLUSIONS

In this paper, we have introduced a fully automatic system for bilateral filtering MR images based on a bilateral neural network. A wide variety of simulated T1weighted MR Images from the BrainWeb dataset were used to train and evaluate the proposed automatic filtering system and it can be implemented in future.

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