AN INTELLIGENT APPROACH TO IMAGE DENOISING

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ABSTRACT

Images are often received in defective conditions due to poor scanning and transmitting devices. Consequently, it creates problems for the subsequent process to read and understand such images. This paper presents a novel recursive intelligent approach based on cellular neural network (CNN) to denoise an image even in the presence of very high ratio of noise. Image denoising is devised as a regression problem between the noise and signals; finally, it is solved using CNN. Accordingly, noises are detected with surrounding information and are removed. Initial experiments show that proposed approach could achieve a higher peak signal-to-noise ratio (PSNR) on images. The proposed algorithm exhibits promising results from quantitatively and qualitatively points of view.

Keywords: *Image denoising, wavelet, parameter selection, CNN, PSNR.*

1. INTRODUCTION

In everyday life, digital images processing have many applications it includes digital cameras, intelligent traffic monitoring, handwriting recognition on checks, signature validation and so on. However, it is not uncommon that images are contaminated by noise due to several unavoidable reasons. Poor image sensors, imperfect instruments, problems with data acquisition process, transmission errors and interfering natural phenomena are its main sources. Therefore, it is necessary to detect and remove noises present in the images. Reserving the details of an image and removing the random noise as far as possible is the goal of image denoising approaches [1].

On the other hand, image denoising from natural and unnatural images is still a challenging problem in image processing. Indeed, wavelets transform based approaches have efficient noise reduction ability in photographic images [5,11,12] and promising results are reported in these references. Recently, multiple wavelets basis image denoising methods are also reported with remarkable performance [14,15]. However, still these approaches have problems on a heavy noisy network [4, 5]. Additionally, wavelet based approaches are computationally expensive and are not suitable for non-natural images [2, 3].

To overcome limitations of wavelet/ multi-wavelet based image denoising techniques, few researchers have introduced intelligent techniques to image denoising. These intelligent approaches exhibit promising results for natural and non-natural (document) images [4].

The focus of this research is to denoise a source image either photographic or document image affected by additive white Gaussian noise. However, it is a valid assumption for images obtained through transmitting, scanning or compression.

The research paper is further organized into three sections. Section 2 presents a briefing on CNN based denoising approach. Experimental results and analysis are conducted in Section 3 and conclusion is drawn in Section 4.

2. CELLULAR NEURAL NETWORK

Image processing tasks are highly processing demanding. However, serial processing is not suitable for real-time processing applications. Cellular neural networks (CNN) are a parallel computing paradigm similar to neural networks, with the difference that communication is allowed between neighboring units only. It has been intensively used in several applications such as image processing, pattern recognition, signal processing and proved to be very useful in real time image processing. Additionally, due to the parallel processing computational time reduced significantly [6,16]. The denoising algorithm reported in this paper, investigates latency properties of CNN along with popular numerical approximation algorithms reported in [7]. Accordingly, Chua and Yang [7,8] derived dynamic equation $C(i,j)$ for an $M \times N$ cellular neural network as under and exhibited in figure 1.

$$C\frac{dx_{ij}(t)}{d_t} = -\frac{1}{R_x}x_{ij}(t) + \sum_{C(k,l)\in N_r(i,j)} A(i,j;k,l)y_{ki}(t) + \sum_{c(k,l)\in N_r(i,j)} B(i,j;k,l)u_{kl} + I \qquad (1)$$

$$y_{ij}(t) = \frac{1}{2}\left[\left|x_{ij}(t)+1\right| - \left|x_{ij}(t)-1\right|\right], 1 \le i \le M, 1 \le j \le N \qquad (2)$$

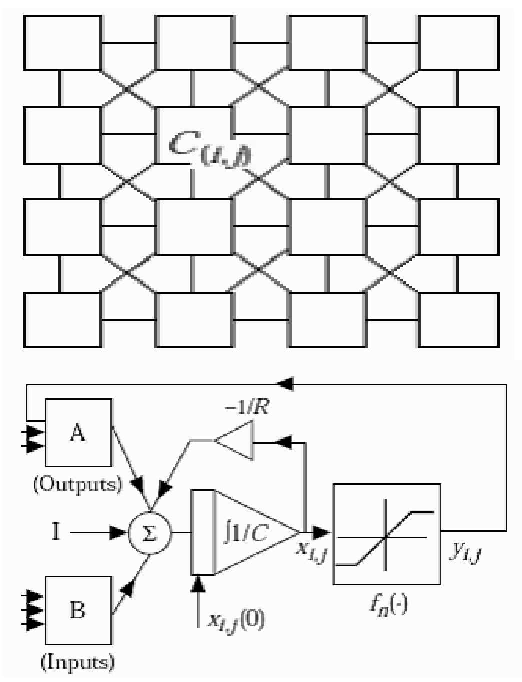

Figure1. Processing of Cellular Neural Network

Where x_{ij}, y_{ij} and u_{ij} are the voltage state, output voltage and input voltage with function of time respectively. R_x is a linear resistance, C is a linear capacitor. $A(i,j;k,l)$ and $B(i,j;k,l)$ are the cloning templates of CNN and are the transconductance of the output and input voltage $C(k,l)$ with respect to $C(i,j)$. $N_r(i,j)$ denotes the r^{th} neighbor of $C(i,j)$ and I is an independent current source. Equation 2 exhibit that output voltage is nonlinear. Accordingly, equation (1) can also be written as

$$c\frac{d_{x_{ij}}(t)}{d_t} = -f\left[x_{ij}(t)\right] + g(t) \qquad (3)$$

$$where,\ f\left[x_{ij}(t)\right] = \frac{x_{ij}(t)}{R_x}$$

$$g(t) = \sum_{\substack{c(k,l)\in N_r(i,j) \\ c(k,l)\neq c(i,j)}} A(i,j;k,l)y_{kl}(t) + \sum_{c(k,l)} B(i,j;k,l)u_{kl} + I$$

2.1 CELLULAR NEURAL NETWORK BASED DENOISING ALGORITHM

Consider an affected image as a noisy image block (NIB), divided into image blocks (IB). Each image block (IB) is further subdivided into several pixel blocks (PB), which are elementary objects to be denoised. Noised image block (NIB) is fed to CNN based algorithm for its further processing as shown in Figure 2.

$$SR\_denoise(NIB) \leftrightarrow$$
$$\forall IB \in NIB(\mathrm{var}(IB) > \alpha \rightarrow SR\_denoise(IB) or$$
$$\forall PB \in IB(noise\_percent(PB) > \beta_2 \rightarrow Fill(PB, meancolor(IB))$$
$$\beta_2 \ge noise\_percent(PB) > \beta_1 \rightarrow Fill(PB, meancolor(PB))$$
$$\beta_1 \ge noise\_percent(PB) \rightarrow \mathrm{int}erpolate(PB))$$

Figure 2: Algorithm for image denoising

The difference in color in image block is a strong clue of the existence of noise. Accordingly, parameter α decides to call recursive CNN to denoise the image block based on denoising algorithm. However, denoising algorithm is not applicable to small noised image block. The value of α is a percentage of color variance of an image block. The denoising algorithm is called recursively provided that the color variance of image block is greater than the threshold value α .
Otherwise, the algorithm further divides an image block into several pixel blocks in the CNN cell. In case the signal to noise ratio is high, the noise cannot be identified from the surrounding colors. To overcome this limitation both threshold are adjustable. Each pixel block is evaluated, if the noise to signal ratio is more than β2, an average of

color block is used. However, if the entire pixel block is noisy, an average of image block color is used. The noise in the pixel block is simply counted and the denoised function simply fills the pixel block with the surrounding color. On the other hand, in case percentage of signal to noise ratio is still higher than β1, an average of pixel block color is employed. However, if the percentage of signal to noise ratio is less than β1, surrounding pixels and cells are manipulated.

In this research, a bi-linear interpolation technique is employed to manipulate pixel block (PB). To reduce the block effect, proposed CNN based image denoising algorithm is recalled. Three thresholds are defined α, β1 and β2 with the following combinations.

α = 55, 65, 70, 85
β1= 60, 75, 80, 85, 90
β2= 93

The usage of mean color is tested by threshold β2. The average color is employed to remove the noise except block is completely noisy. Therefore, threshold value is significantly high. Incase β1< β2, β1 is selected accordingly. To cover a wide spectrum and to check the color variance, threshold α is employed. These thresholds are selected empirically, following experiments on 500 images. It is found that, for α < 70, the average PSNR values of denoised images with respect to other parameters found stable. Therefore, α =70 is selected. To conclude, an average color of an outside block is used unless the percentage of noisy pixels in a pixel block is higher than 93. Finally, if β1 < 60, results are not good. Additionally, peak signal to noise ratio values of the images become stable when the value of β1 becomes 80, 85, or 90. Therefore, α =80, β1=85, and β2=93 selected.

3. RESULTS AND DISCUSSION

In the experiments, images from USC-SIPI database are used [9]. However, there are no document images in the database; therefore, several scanned documents images are used in the experiments. In the literature, recent techniques assume noise model to be Gaussian [1]. Therefore, in the current research noisy image are tested with the Gaussian noise model [10].

Standard criteria reported in the literature for quantitative evaluation PSNR measures are used to measure the quality of the denoised image as well as visual quality of the images. PSNR is defined as the ratio of the variance of the noise-free signal to the mean-squared error between the noise-free signal and the denoising signal. PSNR is computed as below.

$$PSNR = 10\log_{10} \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} 255^2}{\sum_{i=1}^{M}\sum_{j=1}^{N} (f(i,j) - f^{\wedge}(i,j))^2}$$

Where $f^{\wedge}(i,j)$ is the denoised image, $f(i,j)$ is the original noisy image. $M \times N$ is the size of an image.

The proposed technique is implemented using MATLAB 7.0. The test set composed of Lena, Girl, Goldhill and Pepper images taken from USC-SIPI [9], which are widely used in the image processing literature. Accordingly, Gaussian noise is introduced at different ration using MATLAB imnoise function [10]. Experimental results on some of the test images, introduced with gradually high ratio of noise are presented in Figure 3. The first row in the figure 3 represents noisy images and second row presents output of the proposed approach. Additionally, figure 4 exhibits blocks of noise and their removal. The proposed approach is tested at different noise levels. The PSNR results are tabulated in Table 1, collected by average of five times. Accordingly, Table 1 presents results on test images with different noise ratio.

Figure 3: Experimental results with different noise variance using proposed approach.

Figure 4: Noise blocks detection and removal using proposed approach

Table 1: Experimental results of the proposed approach with different noise ratio

Images	Noise Ratio (%)	PSNR (dB)
Lena	53.92	32.15
Girl	72.61	29.62
House	80.73	31.57
Peeper	89.30	23.31

4. CONCLUSION

In this paper, we have presented an intelligent approach based on cellular neural network for adaptive noise denoising. Experimental results of proposed intelligent denoising algorithm exhibit high performance in PSNR and visual effect in color images even in presence of high ratio of noise. In future, we will extend this research to video framework image denoising and image restoration.

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